Essays on intergenerational transfers: Investigating differences between older immigrants and natives

Jongseong Lee

Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
under the Executive Committee
of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2023

Abstract

Essays on intergenerational transfers: Investigating differences between older immigrants and natives

Jongseong Lee

This dissertation consists of three papers on intergenerational transfers and associated differences between immigrant and U.S. native-born (native) families. The first paper investigates differences in intergenerational transfers between immigrant and native families. The second paper examines the impacts of life events on intergenerational transfers and corresponding differences between immigrant and native families. Lastly, the third paper investigates the impacts of the U.S. Social Security program on intergenerational transfers and associated differences between immigrant and native families.

Table of Contents

List of Tables

List of Figures

Acknowledgments

Throughout my doctoral course, I have been incredibly fortunate to have Professor Neeraj Kaushal as my advisor. Her support and dedication to my research and life have been instrumental in my success. The guidance and encouragement she provided have been invaluable and will remain with me throughout my life. I am deeply grateful for her role in shaping this work and my doctoral journey.

I would also like to express my gratitude to Dr. Qin Gao, Dr. Robert Hartley, Dr. Adina Zeki Al Hazzouri, and Dr. Kanghyock Koh for their willingness to serve on my dissertation committee. Their thoughtful feedback and insightful comments on my thesis proposal have significantly enhanced the quality of my research.

My appreciation extends to the Columbia School of Social Work and its Ph.D. program, particularly Ms. Jessica Troiano, for their commitment to ensuring the success of doctoral students. I am also grateful to the Center on Poverty and Social Policy for broadening my perspective on policy research in the United States. Furthermore, I am thankful to the U.S. Department of State and the Fulbright program for providing me with the opportunity to pursue my doctoral studies.

I am grateful to my colleagues at the South Korean Ministry of Health and Welfare. My ten years of experience as a deputy director in the policy area provided the inspiration for my Ph.D. journey. South Korea confronts unprecedented demographic transformations unparalleled by any nation across the globe. It is my fervent aspiration that the profound insights and expertise I have cultivated throughout my doctoral journey will play an instrumental role in transmuting these formidable challenges into fertile grounds for innovation and advancement.

I express profound gratitude to my esteemed mother, Mrs. Dongok Kim, whose unwavering concern. Her unwavering trust in my choices and unparalleled support have been a constant source of strength. I also express gratitude to my late father, Dr. Junyoung Lee, whose cautionary advice about the challenges of academia proved valuable. My heartfelt appreciation extends to my sister, Mrs. Jiyeon Lee, my brother-in-law, Mr. Euntaek Choi, and my adorable nephew Yuju Choi, for their tireless efforts in filling the void I left in Korea. Additionally, I am thankful to my revered father-in-law, Mr. Gyujung Shim, esteemed mother-in-law, Mrs. Geumsuk Kang, and supportive sister-in-law, Ms. Jinah Shim for their dedication and support.

Above all, my profound gratitude is reserved for my wife, Dr. Sunah Shim, whose unwavering support has been the guiding force throughout my doctoral journey. Without her selfless sacrifices, I would not have had the ability to undertake and complete my doctoral program. I find myself incapable of finding the apt expressions, but the time we will share together in the future will serve as the ultimate testament. I would also like to thank my beloved little ones, Gio Lee and Siwoo Lee, who are my world. I will always stand by their side. Any errors, deficiencies, or problems in this dissertation are my faults, but my doctoral dissertation is dedicated wholeheartedly to my family.

Introduction

Demographic changes tied to rising life expectancies and falling birth rates have increased old-age dependency and imposed heavy fiscal burdens on social policy systems (OECD, 2022). A growing volume of public assistance following recent macro-level crises (e.g., the COVID-19 pandemic) has also sharply increased fiscal deficits and public debts, raising concerns about the long-term sustainability of social security systems for the aged. Under these conditions, intergenerational transfers become a key form of support for parents and their children. Such transfers are particularly critical for foreign-born older adults who on average receive low levels of Social Security benefits on account of their limited work histories and low wages. Cultural norms in immigrant families create expectations for intergenerational transfers and family-based care. Yet, there is not much research on intergenerational transfers in immigrant families despite their growing share in the U.S., leaving a gap in our understanding of this important issue. My dissertation addresses this gap through three essays utilizing data from the Health and Retirement Study (HRS) between 1996 and 2018 years. These essays explore differences in intergenerational transfers between immigrant and U.S. native-born (Paper 1), the impact of individual life events on intergenerational transfers (Paper 2), and the impact of public policy (Paper 3) on intergenerational transfers across immigrant and native populations.

The first paper, "Intergenerational transfers: A descriptive study of immigrant and native-born families," investigates differences in intergenerational transfers – from parent to children and from children to parents – between immigrant and native families. Findings suggest that immigrants are generally more involved in child-to-parent (upstream) and parent-to-child

(downstream) transfers than comparable natives, with a larger immigrant-native difference in upstream transfers than in downstream transfers.

The second paper, “Intergenerational transfers in immigrant and native families: Do life events matter?,” examines the impacts of individual life events on intergenerational transfers and corresponding differences between immigrants and natives using two-way fixed effects models. The findings show that a relatively larger number of transfer recipients' life events are associated with intergenerational transfers than transfer donors' life events. Immigrant and mixed-status families exhibit greater responsiveness to transfer recipients' life events compared to their native counterparts.

Finally, the third paper, “U.S. Social Security program and intergenerational transfers of immigrants and native-born citizens,” investigates the impacts of Social Security Early Eligibility Age (age 62) on intergenerational transfers and associated immigrant-native differences. I employ a Regression Discontinuity Design (RDD) and find that children in immigrant families decrease child-to-parent transfers in response to the Social Security program while children in U.S.-born families do not. These effects are particularly pronounced for low-income groups. This suggests Social Security's role in alleviating the financial burden on the children of immigrants.

Paper 1: Intergenerational transfers: A descriptive study of immigrant and native-born families

1. Introduction

The United States hosts the largest immigrant population in the world with more than 45 million immigrants (Migration Policy Institute, 2023). Immigrants are relatively more vulnerable than native-born citizens (hereafter "natives") due to higher levels of poverty, lower educational attainment, limited English proficiency, reduced income and wealth, and a weaker understanding of U.S. institutions (Amuedo-Dorantes & Pozo, 2015; Borjas & Chiswick, 1985; Huang et al., 2021; McKernan et al., 2014). In turn, immigrants are less likely than natives to qualify for U.S. social support programs that are linked to employment (e.g., Social Security). Shorter work histories and a likelihood of being undocumented (either now or in the past) limit immigrants' eligibility for benefits (Amuedo-Dorantes & Pozo, 2015). Immigrants are thus more susceptible to economic and health shocks than natives and are more likely to seek familial help. Intergenerational transfers—transfers from parents to children and from children to parents—hence represent a more important private safety net for immigrant families than for native families. Familial support may also be higher within immigrant families due to cultural factors (Albertini et al., 2019). Certain questions arise in this context: 1) how does intergenerational support occur within immigrant families in the United States?; 2) does this support differ from intergenerational support in native families?

To answer these questions, this paper investigates the immigrant–native differences in intergenerational transfers between older parents and their adult children using data from twelve

survey waves of the Health and Retirement Study (HRS) between the years 1996 and 2018. This work aims to address three knowledge gaps. First, to my knowledge, this is the first study to investigate the immigrant–native gaps in intergenerational transfers in the United States. Other scholars have focused on differences in intergenerational transfers by race and/or ethnicity, which is distinct from immigration status. Second, this study estimates downstream (parent-to-child) and upstream (child-to-parent) transfers. Most prior studies in the United States have solely considered downstream financial transfers from parents to young children (e.g., McGarry, 2016; Schoeni, 2002; Zissimopoulos et al., 2020). Third, this research describes several types of intergenerational transfers to holistically reflect transfer decisions and to clarify connections among financial and non-financial transfers (i.e., informal care provisions). Past researchers have either analyzed parent-to-child transfers or child-to-parent transfers (Brandt & Deindl, 2013; Litwin et al., 2008). A joint analysis of different intergenerational transfers is accordingly lacking.

Understanding the immigrant–native differences in intergenerational transfers in the United States is important from a policy perspective. Demographic changes resulting from immigration and aging call for more awareness of heterogeneity in intergenerational transfers across immigrant and native families. The increase in adult life expectancies could potentially lead to a longer duration of living with disease and disability, thereby prolonging the demand for assistance from adult children to their older parents. Decreasing fertility rates have also resulted in fewer children to take care of their parents (U.S. Department of Health and Human Services, 2022). These shifts have altered the financial and time-based resources transmitted across generations: some older parents may no longer be sufficiently supported by the family safety net, and they may rely instead on public assistance to secure their own and/or their children's lives. Examining patterns in intergenerational transfers can help reveal potential targets for public assistances.

2. Literature review

Theoretical considerations

Theoretically, two competing hypotheses suggest that immigrants display distinct patterns of intergenerational transfers from those of natives (Bordone & de Valk, 2016; Wolff, 2019). The first hypothesis (the so-called "solidarity hypothesis") draws on the belief that cultural and social norms lead to greater cohesion and intergenerational support in immigrant families (McDonald, 2011; Nauck, 2001). Immigrants tend to emphasize families as collective units and cultural norms around filial obligations are often embedded within the family (Kagitcibasi, 2005). Family solidarity also grows as they move from their home to host country (Dumon, 1989).

The cultural-conflict hypothesis, on the other hand, asserts that family support relations may be more fragile among immigrants and their children (Merz et al., 2009). Familial relationships could develop strains due to the immigration process and subsequent adjustment in the host country. There could be intergenerational and intercultural conflicts between the first-generation (e.g., foreign-born parents) and second-generation (e.g., U.S.-born children) family members. The effects of immigration status on transfer behaviors therefore require empirical investigation.

Financial transfers

No U.S.-based research, to my knowledge, has investigated the immigrant–native differences in intergenerational financial and non-financial transfers. The literature has primarily scrutinized determinants of intergenerational transfers. Findings suggest that the amounts and likelihood of transfers are associated with sociodemographic characteristics, namely income, age,

educational level, family composition and relationships, and parents' living status (Cox & Rank, 1992; Laferrère & Wolff, 2006). However, the differences in intergenerational transfers between immigrants and natives remain relatively understudied and unconsidered.

With respect to financial transfers, most U.S. studies have investigated racial and ethnic differences in intergenerational transfers (Cox & Rank, 1992; McGarry & Schoeni, 1995). McKernan et al. (2014) observed that Black and Hispanic families received fewer private financial transfers than White families. Berry (2006) studied racial and ethnic differences in financial transfers from parents to children using HRS data in the year 1994. Children in Black families received fewer transfers from their parents than children in White families, and parents' economic resources strongly accounted for lower support in Black families (Berry, 2006). Yet race and ethnicity are not analogous to the immigrant–native category, especially in the United States; natives and immigrants can be of any race.

Further, prior studies in the United States has typically exclusively examined downstream financial transfers from parents to children (Altonji et al., 1992; Cox & Rank, 1992; Hurd et al., 2011; McGarry, 2016). Neglecting the bilateral aspect of transfers (i.e., both parent-to-child and child-to-parent transfers) fails to fully contextualize families' transfer decisions. According to the two-side altruism model (e.g., Laitner, 1997), if parents encounter income loss, they may respond by reducing financial support to their children (downstream transfers); children may simultaneously respond by offering their parents financial support (upstream transfers).

In the case of immigrant families, some studies have suggested that intergenerational support from children to parents is likely for two reasons: 1) expectations regarding support from children tend to be stronger among immigrant parents (Wolff, 2019); and 2) older parents who are first-generation immigrants often have short employment histories, hence are in greater need for

family support (Albertini et al., 2019). This study empirically investigates whether such beliefs are reflected in financial transfer decisions.

Non-financial transfers

Studies on immigrant–native differences in non-financial transfers (i.e., informal care provisions) have mainly been conducted in the European context, and results are inconclusive (Bordone & de Valk, 2016; Deindl & Brandt, 2011; König et al., 2018). Bordone and de Valk (2016) found that immigrant families provided more upstream (i.e., elder care) and downstream (i.e., grandparenting) care provision than native families based on Survey of Health Ageing and Retirement (SHARE) data. Other studies based on the same SHARE data indicated no significant variation in downstream and upstream care provisions by nativity/immigration status (König et al., 2018). Still others have identified less upstream care among immigrant families than native families (Deindl & Brandt, 2011). In addition to these discrepant findings, it is challenging to extend patterns of behavior among immigrants in Europe to the United States because immigrants in Europe may behave differently from immigrants in the U.S., specifically on account of differences in eligibility for public programs for the elderly across the Atlantic (Antecol et al., 2006; Chiswick et al., 2008).

Many U.S. studies on care provisions have examined differences in non-financial transfers across racial groups. One U.S.-based study reported differences between immigrants and natives in self-reported care "responsibility", not the actual transfer behavior (Florian & Casper, 2016). They found that native grandparents had 2.4 times greater odds of claiming responsibility for

grandchildren than immigrant grandparents. Care responsibility is not equivalent to actual care provision, so further empirical evidence on realized care as non-financial transfers is warranted.

A few studies suggest that co-residency could be viewed as a non-financial intergenerational transfer that serves as a support for family members experiencing economic or physical vulnerability (Bitler & Hoynes, 2015; Cherlin et al., 2013; Wiemers, 2014). Such studies have presented consistent results; immigrant families demonstrate higher co-residency than natives (Raymo et al., 2019; Vega, 1990). However, a recent study of Glick and Hook (2007) noted that differences in the extent of co-residency between immigrant and native groups disappeared when controlling for individuals' and families' economic situations in certain cases. Detailed measures on economic resources (i.e., income and assets) enable us to test the validity of earlier findings on co-residency.

This paper makes three major contributions to the literature. First, to my knowledge, this study offers the first empirical investigation of the immigrant–native differences in intergenerational transfer decisions in the United States. Second, this study investigates both downstream and upstream transfers. Third, to thoroughly describe transfer behavior, this study examines both financial transfer (parent-to-child vs. child-to-parent), and care provision (grandparenting vs. elder care). Sensitivity checks are also conducted using different samples, measures, and methods.

3. Data

This paper uses data from twelve survey waves of HRS files merged with the RAND version of HRS imputation files between 1996 and 2018. The HRS is a nationally representative panel survey of Americans aged 50 and above. HRS provides details on demography, employment, income, wealth, health status, family and social relationships, and financial transfers. Data have been collected primarily every two years since 1992. HRS data contain missing values in income and wealth measures. The RAND Corporation has developed an imputation procedure to compute these values (Hurd et al., 2011). The empirical analysis in this study is based on the RAND version of the data.

HRS data are uniquely suited to this research for several reasons. First, the sample size is more adequate than smaller surveys for estimating transfers for smaller populations such as immigrants. Respondents' children are mostly over age 18 (e.g., 98.1%) and are likely to perform inter-vivo transfers using their own resources. Sufficient sample size can enhance a study's external validity, especially when investigating subgroups such as immigrants. Second, the HRS features child-specific information, leading to more complete transfer reports than other surveys. It is also likely to capture accurate inter-vivo transfers instead of allowances or educational expenses.

4. Sample

The current study uses a parent–child dyad to control for parent and child characteristics, following Goda et al. (2011). For the purpose of this study, a parent is the survey respondent in

the HRS, and a child is an adult-child, who is 18 or older, and the child of the HRS respondent. The parent in the dyad is the head of the household.

The study limits the sample to parents and children who are not co-residents. The study excludes co-resident children from the sample to address potential measurement errors in transfer behaviors. For example, co-residency could be a form of in-kind transfer during economic shocks (Bitler & Hoynes, 2015; Cherlin et al., 2013; Wiemers, 2014). Besides, it is not possible to correctly measure intergenerational transfers within families where parents and children are co-residents (e.g., shared living cost vs. financial transfer) (Isengard et al., 2018). Yet, excluding the co-resident child can also create a selection bias on account of the differences in residential patterns of immigrant and native families with the high probability of co-residence in immigrant families (Bitler & Hoynes, 2015; Cherlin et al., 2013). The final sample includes 56,509 unique parent–child dyads, and a total of 275,599 recode-period observations during the sample periods.[1] For a robustness check, this study also presents estimates based on a sample that includes co-resident families to check whether such biases exist or not.

5. Measures

Outcomes

This study investigates financial and non-financial transfers (i.e., care provisions) to comprehensively depict intergenerational transfer patterns. The primary outcomes of interest are two types of financial transfers: those from parent to child (downstream) and those from child to parent (upstream). In the HRS, respondents are asked to report how much money they or their

[1] This final sample does not include 34,557 dyads, which represent 8.9% of the total observations that include co-resident family.

spouse received from their child and how much they have given to their child in the last two years. The amounts of transfers are measured in U.S. dollars and are CPI-adjusted based on the 2018-year value.

Next, the study explores the probability of non-financial intergenerational transfers in the form of care provision. Regarding care provision from parent to child (downstream), this study uses a dichotomous variable equal to 1 if a parent had helped care for grandchildren in the past two years (and 0 otherwise). To define the child-to-parent transfer (upstream), this study uses a dummy variable equal to 1 if an adult child had provided any hours or days of help to a parent experiencing functional limitations in the last two years (and 0 otherwise).[2] In the analysis of downstream non-financial transfers, the sample is restricted to parents with grandchildren. In the analysis for upstream non-financial transfer, the sample is restricted to parents needing assistance with ADLs/instrumental ADLs.[3]

Predictors

The main variable of interest is immigration status. The current study uses a dichotomous variable equal to 1 if at least one parent is foreign-born (immigrant), otherwise 0. If one parent is native-born and the other is foreign-born, a family is identified as an immigrant family. This definition covers all single and two-parent (couple) households in the sample.

Previous research shows that mixed-status families have different wealth patterns (e.g., Amuedo-Dorantes & Pozo, 2015; Cobb-Clark & Hildebrand, 2009) and these patterns could affect

[2] Functional limitations involve activities of daily living (ADLs) or instrumental ADLs (IADLs). ADLs include activities such as walking, dressing, and bathing. IADLs include relatively more complex self-care activities that involve housekeeping, shopping, and transportation management.
[3] I additionally limit the sample to parents aged over 60, 70, and 80, respectively. Results remain similar to the main estimates.

income streams and therefore transfers. For example, Amuedo-Dorantes and Pozo (2015) found that mixed-status households closely resemble native households in total wealth but are similar to immigrant households in terms of home ownership. In an additional analysis, this study categorizes three family types according to the nativity of the parent's household: both parents are U.S.-born, both parents are foreign-born, and mixed-status (one parent is U.S.-born and one is foreign-born). In this analysis, the sample is restricted to two-parent (couple) households because mixed-status families could not be identified in single-parent households.

Explanatory variables

HRS collects detailed data on parent (household head) characteristics that include age, educational status, marital status, number of children, race and ethnicity, employment status, and household income and wealth, which are controlled in the regression analysis. In the analytic sample, 13.2% of the respondents had negative and zero wealth. This study uses an inverse hyperbolic sine transformation form of household net wealth to deal with negative and zero values (Burbidge et al., 1988). The inverse hyperbolic sine transformation does not drop observations with negative or zero values while a log transformation drops these observations. Prior studies presented that negative or zero values in net wealth were disproportionately large for immigrants (Cobb-Clark & Hildebrand, 2006). This method thus addresses biases from a skewed distribution.

HRS also collects data on the children of older parents, namely age, gender, educational status, number of children, marital status, employment status, and income, which are controlled in the regression analysis. HRS data on children's income is a categorical variable measuring income within four income categories from the 1996 wave onwards. For a more straightforward

interpretation, the current study uses an imputed value of income calculated as the median income within the given range in the March Current Population Survey (CPS), following methods developed by Haider & McGarry (2012). The distribution of imputed income using this method is comparable to the distribution for a similarly aged sample in the CPS (McGarry, 2016). As a sensitivity check, this study presents results based on the original variable in HRS as well as the hot-deck imputation method with CPS (Gustman et al., 2012).

6. Analytic Strategy

Financial transfers

The current study employs a two-part model developed by Cragg (1971) for financial transfers. A methodological concern in this study is a high frequency of zeros in the total amount of financial transfers (i.e., 80.3%). Ordinary least squares (OLS) regression does not provide consistent parameter estimates in this case because the sample that has been censored is not representative of the overall population (Belotti et al., 2015; Heckman, 1979). To circumvent biased estimation, I use a two-part model that fits two processes into one model—in this instance, the decision to transfer (logistic regression) and the level of transfer conditional on positive transfer values (OLS regression). Transfer probability is fitted as shown in Equation (1), after which a logged amount of transfers is set to be conditional on positive values (Equation [2]). The current study starts with parent-to-child financial transfers.

$$\text{Ln}\left(\frac{Pr(Tr_{ict})}{1-Pr(Tr_{ict})}\right) = \alpha + \beta * Immi_i + \varphi P_{it} + \gamma C_{ct} + \mu_t + \varepsilon_{ict} \quad (1)$$

$$\text{Ln}\,(Tr_{ict}) = \alpha^1 + \beta^1 * Immi_i + \varphi^1 P_{it} + \gamma^1 C_{ct} + {\mu^1}_t + {\varepsilon^1}_{ict}, \quad where\ Tr_{ict} > 0 \quad (2)$$

where $Pr(\ Tr_{ict})$ denotes the likelihood of financial transfer from a parent (i) to a child (c) at wave (t). Ln (Tr_{ict}) represents the logged amount of financial transfer from a parent (i) to a child (c) at wave (t) that excludes zero values. β (in equation 1) and β^1(in equation 2) are the coefficients of interest that present the immigrant-native differences in transfers. $Immi_i$ denotes a dichotomous variable indicating 1 if a parent's household is an immigrant family. In the supplementary analysis using the second definition with three family categories, this study adds a dummy variable indicating 1 if a family category is a mixed-status family (a native family is a reference group), in addition to the dummy indicating that both parents are foreign-born. P_{it} and C_{ct} are vectors of demographic characteristics for parent (i) and child (c), respectively. μ_t denotes a time (wave) fixed effect. Robust standard errors are clustered on the parent level. All analyses are weighted using HRS parents' household weights.

Further, the current study analyzes child-to-parent transfers using models similar to those in equations (1) and (2). In this analysis, $Pr(\ Tr_{ict})$ denotes the likelihood of financial transfer from the child (c) to the parent (i) at wave (t). Ln (Tr_{ict}) represents the logged amount of financial transfer from the child (c) to the parent (i) at wave (t). Definitions of all other variables are identical to those in Equations (1) and (2).

Non-financial transfers

Next, this study uses a logistic regression model to estimate probabilities of non-financial transfers as shown in Equation (3) below.[4] Notably, the sample in the analysis of downstream transfers (for grandchild care) is limited to parents with grandchildren, and for upstream transfers

[4] The level of care provisions (e.g., time amount of caring) is not analyzed here due to substantial missing values in HRS.

(for elder care) to parents requiring help with ADL/IADLs. The current study uses subscript (*n*) to distinguish coefficients from Equations (1). The study starts with a non-financial transfer from parent to child, in the form of grandchild care.

$$\text{Ln}\left(\frac{Pr(\,Tr_{ict})}{1-P\ (\,Tr_{ict})}\right) = \alpha_{(n)} + \beta_{(n)} * Immi_i + \varphi_{(n)}P_{it} + \gamma_{(n)}C_{ct} + \mu_{t(n)} + \varepsilon_{ict(n)} \qquad (3)$$

where $Pr(\,Tr_{ict})$ denotes the likelihood of grandchild care from a parent (*i*) to a child (*c*) who had at least one grandchild at wave (*t*). Definitions of all other variables are identical to those in Equation (1). This study also analyzes child-to-parent transfers (e.g., elder care) using the same model as that in Equation (3): $Pr(\,Tr_{ict})$ denotes the likelihood of caring provision from the child (*c*) to the parent (*i*) who experiences any limitations with ADLs or IADLs at wave (*t*). Robust standard errors are also clustered on the parent level and (parent) household level weights in HRS are used in all regressions.

7. Results

Descriptive analysis

Table 1.1 presents descriptive statistics of the main sample, which consists of non-coresident parent–child dyads where the parents have at least one child older than age 18. Panels 1-3 of the table show three distinctive transfer patterns (Column 1). First, immigrant parents are more likely to receive money from their children (upstream) but less likely to send money to their children (downstream) than natives. The average amounts of immigrants' upstream and downstream transfers exceed those of natives. Second, parent-to-child (downstream) transfers are generally more common than child-to-parent (upstream) transfers for both immigrants and natives.

Third, non-financial transfers present trends similar to financial transfers (Panel 3): immigrants demonstrate greater upstream (elder care) and lower downstream (grandchild care) transfers than natives.

Trends in the immigrant-mixed status-native category are also similar to those in the main sample for both financial and non-financial transfers. Column 2 shows immigrants' higher upstream and lower downstream transfer probabilities for mixed-status and native individuals. Additionally, a sample that includes a co-resident family sample displays the same differences by types of families and transfers (see Appendix Table A1.1).

Panels 4 and 5 show that adult children and their older parents in immigrant families had less income, fewer years of education, a lower age, and a lower employment rate than those in native (or mixed-status) families. Such attributes are known to affect transfer decisions (Cox & Rank, 1992; Laferrère & Wolff, 2006). The current study thus investigates whether differences in transfers persisted after controlling for factors indicated in the following sections.

Financial transfers

Table 1.2 has the main analysis results for financial transfers. Columns A, C, E, and G show estimates of transfer probability from Equation (1) based on logistic regression, and Columns B, D, F, and H present estimates of logged transfer amounts (conditional on positive values) from Equation (2) based on OLS regression.

In the immigrant–native family comparison, immigrants display higher downstream and upstream transfers than natives after controlling for covariates and these differences in Column 1.

Specifically, the odds of parent-to-child (downstream) transfers by immigrants are 16.0% higher than those of comparable natives (Column A). Immigrants have 35.8% higher odds of child-to-parent (upstream) transfers than their native counterparts (Column C). Among individuals who make financial transfers, immigrants also send and receive higher amounts of money than comparable natives: 13.9% higher for parent-to-child transfers and 19.9% higher for child-to-parent transfers.

Among the three family categories in Column 2, immigrant families are similarly more engaged in financial transfers than natives, especially for upstream transfers, while mixed status–native differences are statistically insignificant. Specifically, the odds of immigrants' downstream transfers are 5.7% higher than those of natives (Column E) while the odds of immigrants' upstream transfers are much higher than for comparable natives (i.e., 115%) (Column G). In transfer amount ($s), immigrant families send 20.5% and 29.3% more money for parent-to-child and child-to-parent transfers, respectively (Columns F and H). Here also, the immigrant–native difference is much wider for upstream transfers than for downstream transfers.

Robustness check results using a sample that includes coresident families (Table 1.3) are consistent with the main results, but the effect sizes are smaller. A possible selection bias from a high probability of co-residence in immigrants (e.g., Bitler & Hoynes, 2015; Cherlin et al., 2013) does not critically confound the main estimates in Table 1.2. Moreover, the smaller effect sizes observed in this sample suggest that unique features of coresident families (e.g., shared living costs) may lead to a possible downward bias in estimates. For example, shared living costs in coresident families can function as a form of familial financial support (transfer) – but it is not clear whether the transfer is from the parent to the child or child to the parent. This ambiguity can lead to an

underestimation of the true extent of financial transfers among coresident families, which may contribute to the smaller effect sizes observed in the sample that includes coresident families.

To sum up, estimated results underline three major points. First, immigrant families conduct more downstream (parent-to-child) financial transfers than comparable native families. Descriptive statistics (unadjusted for demographics) in Table 1.1 exhibit a lower downstream transfer probability among immigrants compared with natives. However, after controlling for other covariates associated with transfer decisions, this study finds that immigrants' downstream transfer probability is significantly higher than that of comparable natives. Second, immigrants exhibit higher upstream (child-to-parent) transfers than comparable native families (Albertni et al, 2019, Wolff, 2019). Immigrant–native differences in upstream transfers are larger than for downstream transfers. Third, in immigrant–mixed–native family categories, immigrant families with two foreign-born parents demonstrate greater intergenerational financial transfers than mixed-status families with only one foreign-born parent. Mixed-status families are not much different from native families at least in the financial transfers. These findings support the family solidarity hypothesis that posits that greater immigrants' intergenerational transfer patterns are rooted in their cultural norms (Kagitcibasi, 2005) or experiences during the immigration process (Dumon, 1989).

Non-financial transfers

Table 1.4 shows that immigrant families' transfer probability is higher for elder care (upstream) and lower for grandchild care (downstream) than comparable natives in Column 1. The odds of grandchild care (downstream) among immigrants are 8.6% lower than that for natives (Column A) while the odds of elder care (upstream) of immigrants are 11.7% higher than those of natives (Column B).

Similarly, estimates in three family categories demonstrate that immigrants have the highest upstream transfer probability for elder care (i.e., 35% higher odds, Column D) but the lowest downstream transfer probability (grandchild care) (i.e., 17.7% lower odds, Column C) among immigrant-mixed status-native groups in Column 2. Further, smaller (but statistically significant) differences accompany all outcomes between mixed-status and native families compared to those between immigrant and native families. For instance, mixed status-native differences in grandchild care probabilities (e.g., 10.2% lower odds vs. natives) are far smaller than immigrant-native differences (e.g., 17.7% lower odds vs. natives) in Column C, and these two differences (coefficients) are statistically different with 95% confidence level ($p<0.05$.)

Further, robustness check results using a sample that includes coresident families (Table 1.5) reveal consistently smaller differences in outcomes between immigrant and native (and mixed-status and native) families than the main results in Table 1.4, similar to financial transfers. Mixed status–native differences are again smaller than immigrant–native differences in all outcomes.

To sum up, non-financial transfers show several noteworthy findings. First, immigrants in the U.S. are more engaged in elder care (upstream transfer) but less engaged in grandchild care (downstream transfer) than comparable natives. Interestingly, gaps in downstream non-financial transfers between immigrants and natives differ from the gaps in downstream financial transfers (e.g., a higher probability among immigrants than natives). This discrepancy is aligned with immigrants' low responsibility for grandchildren in U.S.-based research (e.g., Florian & Casper, 2016): this responsibility (e.g., perception) seems to be associated with actual transfer behavior (e.g., realized perceptions). Second, the findings suggest that immigrants' intergenerational transfers flow upward, echoing the results for financial transfers. Third, immigrant families with

two foreign-born parents exhibit a higher probability of non-financial transfers than mixed-status families with one immigrant parent with statistical significance at the 95% confidence level ($p<0.05$), mirroring financial transfers. In contrast to the statistical insignificance of mixed status-native differences in financial transfers, those in non-financial transfers are statistically significant; familial caring behaviors of mixed-status families might be not tilted toward those of native.

Co-residency

For a more holistic understanding of familial support behaviors, the current study examines the probability of co-residency (Bitler & Hoynes, 2015; Cherlin et al., 2013). Co-residency is measured as a dichotomous variable equal to 1 if the parent and child had lived in the same house(hold) in the past two years (and 0 otherwise). The analytic model follows the case of non-financial transfers as shown in Equation (3). $Pr(Tr_{ict})$ in the equation denotes the likelihood of co-residency of a parent (i)- child (c) dyad at wave (t). Note that the sample in this analysis additionally covers parent-child dyads in coresident families.

Estimated results in Table 1.6 demonstrate that immigrants are also more inclined to reside with parents or children (co-residency) than natives. The odds of immigrants' co-residency probability are 29.8% higher than those of comparable natives (Column A). In the immigrant-mixed status-native category, differences between immigrants and natives are most pronounced (e.g., 80% greater odds for immigrants vs. natives) while mixed status-native differences are statistically insignificant (Column B). These findings are congruent with most prior studies (Raymo et al., 2019; Vega, 1990), except for Glick and Hook (2007). After controlling for

economic resources (e.g., income, assets), immigrant-native differences in co-residency do not disappear.

Additional Sensitivity checks

One remaining potential source of bias concerns the validity of assumptions in the two-part model (i.e., the independent relationship between one's decision to transfer and the transfer level) (Belotti et al., 2015). The current study analyzes the raw amount of transfers as an additional outcome to determine if large disparities exist between this outcome and that in the primary analysis (e.g., the transfer amount conditional on positive transfer values). The former includes the effects of one's decision to transfer whereas the latter does not. Note that, in this section, this study uses non-logged amount values conditional on positive values for a simple comparison across estimates (vs. logged amount values used in the primary analysis from Tables 1.2 to 1.3). As shown in Panel 1 of Table 1.7, the assumption of the two-part model is less likely to be violated; no great disparities emerge in findings between these two outcomes (Columns A vs. B and E vs. F). The direction and significance of coefficients on immigrant status are identical to those in the primary analysis, irrespective of the impacts of transfer decisions. The two-part model is thus valid in the estimation of this study.

The current study further employs a Tobit model and a Heckman two-stage model to test the validity of estimates from the primary model: the former censors zero observations as corner solutions, and the latter uses two processes (similar to those in the two-part model) but allows correlation between the error terms (Cox & Rank, 1992; Heckman, 1979). If estimates are consistent across models, then the primary estimates might be robust. Panel 2 in Table 1.7 shows

that estimates from the Tobit model are not much different from the initial estimates: the significance and size of coefficients on immigrant status (and other covariates) are not notably different from the original estimates (Columns A vs. D and E vs. H).[5] Results using the Heckman two-stage model (Columns C and G) are also comparable to original estimates from the primary analyses; estimates on child-to-parent transfer are not interpreted because the inverse Mills ratio for this outcome is not statistically significant (Puhani, 2000). These analyses confirm that model selection does not critically affect the overall results.

Next, this study uses two additional measures to test whether the chosen measures of income may bias the main results regarding financial and non-financial outcomes in Table 1.8. Results for hot-deck imputed income (Panels 1-2 and 2-2) and categorical income (Panels 1-3 and 2-3) do not vary much from the original results (Panels 1-1 and 2-1). The magnitude and significance of coefficients on immigrant status (and other factors) are nearly identical to those of the original results irrespective of income type for all outcomes. This pattern implies that potential bias from the income measurement may not be a concern in the current study; different measures of income measurement do not alter primary estimates, in accordance with Haider & McGarry (2012).

The association between intergenerational transfers and poverty status of older parents

The current study is interesting to learn the role of intergenerational financial transfers in lowering poverty among older parents. In this analysis, the study limits the sample of older parents

[5] Results from the Tobit model typically present effect sizes more similar to the main results than those from the Heckman model. The exception to this is the parent-to-child transfer amount under the immigrant-mixed status-native category.

(i.e., core respondents in HRS) to survey waves conducted in the year 2002 or later due to the unavailability of information required for poverty measurement in the earlier waves.

Table 1.9 presents two distinctive findings. First, intergenerational transfers play a larger role in preventing poverty among older immigrant parents compared to older native parents. Older immigrant parents possess fewer economic resources, including income, wealth, and social security benefits, that could serve as a buffer against economic hardship compared to U.S.-born parents (Panel 1). The analysis shows a higher reliance on intergenerational transfers among older immigrants, as reflected in a greater disparity in poverty rates between those who receive transfers and those who do not, compared to native-born parents (Panel 2). Panel 3 further reveals that poverty rates among those who receive transfers are substantially lower when intergenerational transfers are added. The difference between poverty rates with- and without- intergenerational transfer is especially pronounced for immigrants than natives (i.e., -7.3 percentage points for immigrants vs. -3.4 percentage points for natives).

Further, intergenerational transfers function as a form of needs-based familial support. Older parents who receive child-to-parent transfers present higher poverty rates than those who do not, while older parents who provide parent-to-child transfers show lower poverty rates than those who do not (Panel 2). These differences are statistically significant at the 95% confidence level. Transfers are made corresponding to transfer recipients' demands (Laferrère & Wolff, 2006).

8. Discussion and Conclusion

The current study analyzes detailed intergenerational transfers (i.e., downstream vs. upstream and financial vs. non-financial) to provide a holistic picture of differences across

immigrant and native families. Empirical analyses of financial transfers have three important findings. First, immigrants are more engaged in child-to-parent (upstream) transfers and parent-to-child (downstream) transfers than comparable natives. Second, a larger immigrant–native difference is observed in upstream transfers than in downstream transfers. Third, among immigrant–mixed status–native categories, differences between mixed-status and native families are relatively modest and insignificant in most models. Further, estimates of non-financial transfers generally exhibit the same trends as for financial transfers. However, immigrants are less engaged in grandchild care (downstream transfers) than their native counterparts, a finding to which Florian and Casper (2016) alluded in terms of grandchild care responsibilities. This study also finds a higher prevalence of co-residency among immigrants compared to native counterparts. The role of intergenerational transfers as need-based familial support is more critical in preventing poverty among older immigrant parents compared to native-born parents.

Overall, this study's results suggest that immigrants in the U.S. tend to be more engaged in intergenerational transfers (except for grandchild care) than natives, thereby supporting the solidarity theory (McDonald, 2011; Nauck, 2001). Findings also suggest that intergenerational transfers of immigrants mainly flow upward for financial and non-financial transfers in comparison to natives. Arguably, these two main findings together confirm the hypothesis that older immigrants in the U.S. might rely more on familial support than U.S. natives and their immigrant children. Robustness checks using different samples (that include coresident families), empirical models (Tobit and Heckman models), and income measures yield similar findings for financial and non-financial transfers, and co-residency.

Higher intergenerational transfers of immigrants compared to native-born counterparts (e.g., child-to-parent transfer) imply older immigrants' economic vulnerabilities in incomes and

highlight the need to revisit eligibility rules for public assistance programs to support these individuals. Altruism theory suggests that transfers are made in accordance with transfer recipients' demands (Barro, 1974; Becker, 1974; Laferrère & Wolff, 2006). In this study, immigrants are consistently and heavily dependent on familial transfers, which help alleviate economic vulnerability from the high risks of unemployment and low-income occupations in the United States. Yet private transfers are also known to be fairly volatile support sources (vs. public transfers) that depend on transfer donors' economic situations rendering greater volatility to the economic lives of older immigrants (McManus & DiPrete, 2000). To address this economic insufficiency, public transfer programs might revisit eligibility rules. The programs currently set different eligibility criteria that can be more strict for immigrants compared to natives (e.g., qualified aliens' 5-year limited eligibility for the Federal means-test program in 1996 PRWORA) (Kaushal, 2010).

Table 1.1. Descriptive statistics by immigration status

	1. Immigrant-native category		2. Immigrant-mixed status-native category		
	U.S-born (Native)	Foreign-born (Immigrant)	Native	Mixed status	Immigrant
Panel 1. Financial transfers (parent-to-child, downstream)					
Probability	19.0%	17.1%*	21.9%	22.2%*	15.3%*
Amount (>0)	9,172	13,760*	9,508	16,422*	12,991*
Average Amount (including zeros)	1,738	2,348*	2,077	3,653*	1,983*
Panel 2. Financial transfers (child-to-parent, upstream)					
Probability	2.2%	3.5%*	1.2%	1.5%*	4.4%*
Amount (>0)	3,464	3,516*	4,122	2,966*	3,470*
Average Amount (including zeros)	75	121*	49	44*	152*
Panel 3. Non-financial transfer					
Grandchild care (downstream)	13.2%	10.9%*	16.2%	11.9%*	13.5%*
Care of Parents with IADL/ADL (upstream)	2.0%	2.5%*	0.9%	1.1%*	1.8%*
Panel 4. Child's characteristics					
Median household income	60,666	51,943*	63,888	58,500*	49,566*
Imputed household income	52,589	46,916*	53,623	49,999*	44,544*
Categorical household income					
- Less than $10,000	8.5%	14.1%*	7.6%	11.3%*	16.6%*
- $10,000 ~ $34,999	26.1%	28.0%*	25.4%	27.0%	27.8%*
- $35,000 ~ $69,999	54.8%	49.2%*	56.1%	51.9%*	48.3%*
- More than $70,000	10.6%	8.7%*	10.9%	9.8%*	7.3%*
Age	40.9	39.1*	38.7	37.7	36.6*
Years of education	13.8	13.4	14.0	14.0	13.2*
Married	62.6%	61.7%	64.5%	59.0%*	66.7%*
Currently in school	5.6%	6.9%*	6.5%	8.1%*	6.7%
Number of kids	1.7	1.7	1.6	1.4*	1.8*
Gender (Male)	49.6%	48.9%	50.0%	49.0%*	47.2%*
Employed	82.7%	80.4%*	85.4%	83.0%*	80.7%*
Panel 5. Parent's characteristics (head of household)					
Total household annual income	75,432	74,413*	103,472	106,097*	96,866*
Total household wealth	544,555	505,999*	736,177	755,447*	590,047*
Age	68.3	68.0	66.8	66.8	66.4
Years of education	12.6	10.6*	12.9	12.7*	9.7*
Married	53.7%	58.7%*			
Number of kids	4.0	4.5*	4.0	4.3*	4.7*
Employed	40.2%	37.6%*	47.8%	45.9%*	42.7%*
Hispanic	4.1%	44.8%*	3.5%	24.1%*	58.3%*
Non-white	15.7%	29.0%*	10.3%	13.8%*	39.5%*
Num. of observations	237,565	38,034	127,839	10,558	12,478

Note: The sample consists of parent-child dyads where the child is over 18 years old in HRS and not living with the parent in HRS. Column (1) presents descriptive data for the immigrant-native sample and Column (2) for the immigrant-native-mixed status sample limited to two-parent households. Data is sourced from HRS data from 1996 to 2018 years. Asterisk (*) indicates that differences in mean values between immigrant and native (and immigrant-native and mixed status-native in Column 2) are statistically significant with 99% confidence level ($p<0.01$.).

Table 1.2. Association between financial transfers and immigration status

	1. Immigrant-native category				2. Immigrant-mixed-native category			
	Parent-to-child transfer (downstream)		Child-to-parent transfer (upstream)		Parent-to-child transfer (downstream)		Child-to-parent transfer (upstream)	
	(A) Probability	(B) Amount	(C) Probability	(D) Amount	(E) Probability	(F) Amount	(G) Probability	(H) Amount
Immigrant-native category (reference: native-born)								
Immigrant	1.160***	0.139***	1.358***	0.199***				
	(0.028)	(0.020)	(0.056)	(0.043)				
Immigrant-mixed-native category (reference: native-born)								
Mixed status					1.030	0.122	1.000	0.072
					(0.038)	(0.129)	(0.100)	(0.103)
Immigrant					1.057**	0.205***	2.159***	0.293***
					(0.030)	(0.037)	(0.191)	(0.080)
Child's characteristics								
Household l income	0.800***	-0.053***	1.522***	0.115***	0.795***	-0.070***	1.561***	0.187***
	(0.007)	(0.007)	(0.045)	(0.020)	(0.010)	(0.009)	(0.076)	(0.038)
Age	0.676***	-0.126***	1.052	-0.094**	0.646***	-0.156***	1.019	0.025
	(0.014)	(0.017)	(0.039)	(0.043)	(0.021)	(0.026)	(0.053)	(0.080)
Age-squared	1.008***	0.002***	0.999	0.002**	1.009***	0.003***	1.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age-cubed	1.000***	-0.000***	1.000	-0.000***	1.000***	-0.000***	1.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of education	1.029***	0.058***	1.086***	0.048***	1.027***	0.063***	1.074***	0.042***
	(0.004)	(0.003)	(0.009)	(0.007)	(0.005)	(0.004)	(0.016)	(0.012)
Married	0.784***	0.033**	0.720***	-0.097***	0.757***	0.054***	0.676***	-0.115*
	(0.014)	(0.015)	(0.028)	(0.034)	(0.018)	(0.019)	(0.046)	(0.061)
Currently in school	1.508***	0.108***	1.021	-0.073	1.455***	0.125***	1.029	-0.085
	(0.043)	(0.020)	(0.076)	(0.068)	(0.051)	(0.024)	(0.132)	(0.115)
Number of kids	1.096***	-0.009*	0.965***	-0.026***	1.097***	-0.009	0.964*	-0.067***
	(0.006)	(0.005)	(0.011)	(0.009)	(0.008)	(0.006)	(0.021)	(0.017)
Gender (Male)	0.865***	0.018	0.994	0.118***	0.877***	0.016	1.029	0.162***
	(0.012)	(0.012)	(0.029)	(0.027)	(0.016)	(0.015)	(0.052)	(0.050)
Employed	1.080***	-0.085***	1.014	-0.157***	1.082***	-0.068***	0.947	-0.367***
	(0.023)	(0.017)	(0.045)	(0.041)	(0.030)	(0.022)	(0.076)	(0.078)
Parent's characteristics (head of household)								
Household income	1.380***	0.131***	0.919***	0.006	1.445***	0.191***	0.897***	0.014
	(0.024)	(0.005)	(0.005)	(0.007)	(0.027)	(0.007)	(0.009)	(0.012)
Household wealth	1.045***	0.028***	0.966***	0.003	1.040***	0.032***	0.952***	-0.008*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)
Age	0.788***	0.067	0.977	0.855***	0.758***	0.014	1.059	0.287
	(0.038)	(0.047)	(0.087)	(0.155)	(0.048)	(0.057)	(0.172)	(0.313)
Age-squared	1.004***	-0.001	1.001	-0.013***	1.004***	-0.000	1.000	-0.005
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)
Age-cubed	1.000***	0.000	1.000	0.000***	1.000***	0.000	1.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.686***	-0.086***	1.325***	-0.091*	0.727***	-0.101***	1.655***	-0.409***
	(0.022)	(0.029)	(0.069)	(0.050)	(0.029)	(0.036)	(0.155)	(0.082)
Non-white	0.859***	-0.243***	1.931***	-0.070**	0.884***	-0.229***	1.767***	-0.054
	(0.017)	(0.019)	(0.069)	(0.032)	(0.025)	(0.025)	(0.120)	(0.060)
Years of education	1.091***	0.046***	0.970***	0.022***	1.082***	0.043***	0.959***	0.004
	(0.003)	(0.002)	(0.005)	(0.005)	(0.004)	(0.003)	(0.007)	(0.008)
Married	0.887***	-0.035***	0.523***	0.072**	1.303***	0.176***	0.981	0.111
	(0.016)	(0.013)	(0.018)	(0.031)	(0.069)	(0.044)	(0.141)	(0.132)
Number of kids	0.777***	-0.052***	0.937***	-0.046***	0.783***	-0.046***	0.962***	-0.076***
	(0.003)	(0.004)	(0.007)	(0.007)	(0.004)	(0.005)	(0.012)	(0.012)
Employed	0.966*	-0.075***	0.877***	-0.025	0.939***	-0.080***	0.880*	0.053
	(0.018)	(0.015)	(0.037)	(0.034)	(0.021)	(0.018)	(0.060)	(0.057)
Num. of observations	275,599	43,913	275,599	7,409	150,875	27,764	150,875	2,481
R-squared		0.118		0.119		0.128		0.180

Note: The sample consists of parent-child dyads where the child is over 18 years old and not living with the parent in HRS. Each column is based on a separate regression. For parent-to-child transfers, financial transfers include the likelihood of whether an adult child received any money from a parent last two years (logistic regressions, Columns A and E) and transfer amount conditional on positive values (OLS regression, Columns B and F). For child-to-parent transfers, financial transfers include the likelihood of whether a parent received any money from an adult child last two years (logistic regressions, Columns C and G) and transfer amount conditional on positive values (OLS regression, Columns D and H). All regressions are weighted. Data is sourced from HRS data from 1996 to 2018 years. Standard errors are robust clustered on the parent (in parentheses).
*** p<0.01 ** p<0.05 * p<0.1

Table 1.3. Robustness check: Association between financial transfers and immigration status

	1. Immigrant-native category				2. Immigrant-mixed-native category			
	Parent-to-child transfer (downstream)		Child-to-parent transfer (upstream)		Parent-to-child transfer (downstream)		Child-to-parent transfer (upstream)	
	(A) Probability	(B) Amount	(C) Probability	(D) Amount	(E) Probability	(F) Amount	(G) Probability	(H) Amount
Immigrant-native category (reference: native-born)								
Immigrant	1.119***	0.119***	1.346***	0.084**				
	(0.025)	(0.018)	(0.050)	(0.037)				
Immigrant-mixed-native category (reference: native-born)								
Mixed status					0.993	0.078	1.057	-0.048
					(0.034)	(0.076)	(0.093)	(0.087)
Immigrant					1.007**	0.060	2.150***	0.276***
					(0.003)	(0.067)	(0.163)	(0.032)
Child's characteristics								
Household income	0.818***	-0.070***	1.332***	0.083***	0.815***	-0.085***	1.416***	0.117***
	(0.006)	(0.006)	(0.029)	(0.015)	(0.009)	(0.007)	(0.053)	(0.028)
Age	0.781***	-0.167***	0.972	-0.085***	0.814***	-0.169***	0.985	-0.108*
	(0.018)	(0.013)	(0.030)	(0.031)	(0.023)	(0.016)	(0.046)	(0.058)
Age-squared	1.004***	0.003***	1.001	0.002***	1.003***	0.003***	1.000	0.003**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Age-cubed	1.000***	-0.000***	1.000	-0.000***	1.000**	-0.000***	1.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of education	1.046***	0.062***	1.077***	0.038***	1.046***	0.068***	1.055***	0.033***
	(0.004)	(0.003)	(0.007)	(0.006)	(0.005)	(0.004)	(0.013)	(0.011)
Married	0.780***	0.043***	0.653***	-0.150***	0.757***	0.060***	0.589***	-0.172***
	(0.013)	(0.015)	(0.022)	(0.029)	(0.017)	(0.018)	(0.035)	(0.053)
Currently in school	1.534***	0.157***	1.035	-0.068	1.503***	0.176***	1.063	-0.068
	(0.038)	(0.017)	(0.062)	(0.052)	(0.045)	(0.021)	(0.104)	(0.086)
Number of kids	1.104***	-0.000	0.951***	-0.040***	1.106***	0.001	0.939***	-0.082***
	(0.005)	(0.005)	(0.010)	(0.008)	(0.007)	(0.006)	(0.019)	(0.016)
Gender (Male)	0.872***	0.009	1.010	0.113***	0.882***	0.007	1.014	0.151***
	(0.011)	(0.011)	(0.026)	(0.024)	(0.015)	(0.013)	(0.046)	(0.043)
Employed	1.088***	-0.087***	1.080*	-0.189***	1.092***	-0.084***	1.086	-0.371***
	(0.021)	(0.015)	(0.043)	(0.036)	(0.027)	(0.019)	(0.079)	(0.068)
Parent's characteristics (head of household)								
Household income	1.337***	0.118***	0.926***	0.009	1.405***	0.181***	0.909***	0.020**
	(0.021)	(0.004)	(0.004)	(0.005)	(0.025)	(0.007)	(0.007)	(0.009)
Household wealth	1.041***	0.027***	0.969***	0.003	1.033***	0.030***	0.954***	-0.007*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
Age	0.758***	0.044	1.005	0.722***	0.729***	-0.037	1.116	0.339
	(0.036)	(0.043)	(0.087)	(0.123)	(0.041)	(0.052)	(0.180)	(0.226)
Age-squared	1.004***	-0.000	1.000	-0.011***	1.005***	0.001	0.999	-0.005*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Age-cubed	1.000***	0.000	1.000	0.000***	1.000***	-0.000	1.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.688***	-0.110***	1.335***	-0.034	0.722***	-0.116***	1.585***	-0.233***
	(0.020)	(0.025)	(0.061)	(0.042)	(0.025)	(0.030)	(0.130)	(0.067)
Non-white	0.825***	-0.239***	1.874***	-0.062**	0.850***	-0.237***	1.760***	-0.006
	(0.015)	(0.017)	(0.059)	(0.027)	(0.022)	(0.023)	(0.102)	(0.050)
Years of education	1.092***	0.052***	0.974***	0.020***	1.081***	0.051***	0.962***	0.004
	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.007)	(0.006)
Married	0.886***	-0.006	0.520***	0.036	1.262***	0.214***	1.008	0.168
	(0.015)	(0.012)	(0.016)	(0.027)	(0.063)	(0.042)	(0.133)	(0.113)
Number of kids	0.780***	-0.058***	0.907***	-0.053***	0.786***	-0.056***	0.931***	-0.083***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)	(0.011)	(0.011)
Employed	0.993	-0.071***	0.898***	-0.028	0.962*	-0.081***	0.934	0.052
	(0.017)	(0.014)	(0.032)	(0.029)	(0.020)	(0.017)	(0.055)	(0.048)
Num. of observations	310,156	52,757	310,156	9,617	168,672	33,415	168,672	3,192
R-squared		0.137		0.104		0.156		0.147

Note: The sample consists of parent-child dyads where the child is over 18 years old in HRS. Each column is based on a separate regression. For parent-to-child transfers, financial transfers include the likelihood of whether an adult child received any money from a parent last two years (logistic regressions, Columns A and E) and transfer amount conditional on positive values (OLS regression, Columns B and F). For child-to-parent transfers, financial transfers include the likelihood of whether a parent received any money from an adult child last two years (logistic regressions, Columns C and G) and transfer amount conditional on positive values (OLS regression, Columns D and H). Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. Standard errors are robust clustered on the parent (in parentheses). *** p<0.01 ** p<0.05 * p<0.1

Table 1.4. Association between non-financial transfers and immigration status

	1. Immigrant-native category		2. Immigrant-mixed-native category	
	(A) Grandchild care	(B) Elder care	(C) Grandchild care	(D) Elder care
Immigrant-native category (reference: native)				
Immigrant	0.914***	1.117*		
	(0.027)	(0.069)		
Immigrant-mixed-native category (reference: native)				
Mixed status			0.898**	1.246***
			(0.043)	(0.096)
Immigrant			0.823***	1.350***
			(0.037)	(0.098)
Child's characteristics				
Household income	0.973**	0.960**	0.975	0.940
	(0.012)	(0.019)	(0.015)	(0.044)
Age	1.554***	0.883***	1.446***	0.756***
	(0.056)	(0.041)	(0.108)	(0.079)
Age-squared	0.989***	1.003***	0.990***	1.006**
	(0.001)	(0.001)	(0.002)	(0.002)
Age-cubed	1.000***	1.000***	1.000***	1.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Years of education	1.053***	0.996	1.061***	0.990
	(0.005)	(0.008)	(0.006)	(0.018)
Married	0.903***	1.034	0.887***	1.039
	(0.020)	(0.045)	(0.026)	(0.103)
Currently in school	1.099**	1.069	1.081	0.825
	(0.043)	(0.109)	(0.053)	(0.185)
Number of kids	1.128***	1.007	1.122***	1.001
	(0.007)	(0.010)	(0.010)	(0.025)
Gender (Male)	0.695***	0.418***	0.713***	0.482***
	(0.012)	(0.015)	(0.015)	(0.040)
Employed	1.108***	0.950	1.142***	0.916
	(0.027)	(0.040)	(0.034)	(0.092)
Parent's characteristics (head of household)				
Household income	1.017***	0.992	1.030***	0.969
	(0.006)	(0.009)	(0.009)	(0.021)
Household wealth	1.013***	0.991***	1.016***	0.979***
	(0.002)	(0.003)	(0.003)	(0.006)
Age	0.671***	0.500***	0.611***	0.552**
	(0.043)	(0.074)	(0.045)	(0.131)
Age-squared	1.007***	1.009***	1.009***	1.008**
	(0.001)	(0.002)	(0.001)	(0.003)
Age-cubed	1.000***	1.000***	1.000***	1.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.804***	0.803***	0.835***	0.749
	(0.027)	(0.057)	(0.035)	(0.135)
Non-white	1.015	1.281***	0.947*	1.239**
	(0.022)	(0.052)	(0.027)	(0.123)
Years of education	1.032***	0.957***	1.026***	0.931***
	(0.003)	(0.005)	(0.004)	(0.010)
Married	1.539***	0.315***	1.593***	0.854
	(0.028)	(0.015)	(0.093)	(0.165)
Number of kids	0.851***	0.876***	0.836***	0.893***
	(0.004)	(0.007)	(0.005)	(0.015)
Employed	1.007	0.360***	1.021	0.366***
	(0.019)	(0.032)	(0.024)	(0.057)
Num. of observations	213,438	77,594	111,289	31,425

Note: The sample consists of parent-child dyads where the child is over 18 years old and not living with the parent in HRS. Each column indicates each type of non-financial outcome, which is based on a separate logistic regression. Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. Standard errors are robust clustered on the parent (in parentheses). *** p<0.01 ** p<0.05 * p<0.1

Table 1.5. Robustness check: Association between non-financial transfers and immigration status

	1. Immigrant-native category		2. Immigrant-mixed-native category	
	(A) Grandchild care	(B) Elder care	(C) Grandchild care	(D) Elder care
Immigrant-native category (reference: native)				
Immigrant	0.931**	1.104*		
	(0.026)	(0.057)		
Immigrant-mixed-native category (reference: native)				
Mixed status			0.922*	1.208*
			(0.043)	(0.118)
Immigrant			0.828***	1.215*
			(0.036)	(0.116)
Child's characteristics				
Household income	0.950***	0.905***	0.957***	0.868***
	(0.010)	(0.014)	(0.014)	(0.032)
Age	1.526***	0.893***	1.441***	0.867*
	(0.050)	(0.030)	(0.096)	(0.069)
Age-squared	0.989***	1.003***	0.990***	1.003
	(0.001)	(0.001)	(0.002)	(0.002)
Age-cubed	1.000***	1.000***	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Years of education	1.054***	1.003	1.059***	0.995
	(0.005)	(0.006)	(0.006)	(0.015)
Married	0.823***	0.793***	0.820***	0.781***
	(0.017)	(0.028)	(0.022)	(0.061)
Currently in school	1.130***	1.128	1.095**	0.949
	(0.041)	(0.086)	(0.050)	(0.155)
Number of kids	1.107***	0.963***	1.107***	0.943***
	(0.007)	(0.008)	(0.010)	(0.021)
Gender (Male)	0.675***	0.486***	0.693***	0.593***
	(0.011)	(0.014)	(0.014)	(0.040)
Employed	1.115***	0.855***	1.134***	0.813**
	(0.025)	(0.030)	(0.033)	(0.070)
Parent's characteristics (head of household)				
Household income	1.012**	0.994	1.028***	0.971**
	(0.005)	(0.007)	(0.008)	(0.015)
Household wealth	1.011***	0.989***	1.014***	0.976***
	(0.002)	(0.002)	(0.003)	(0.005)
Age	0.724***	0.569***	0.632***	0.652**
	(0.044)	(0.067)	(0.045)	(0.135)
Age-squared	1.006***	1.007***	1.008***	1.005*
	(0.001)	(0.002)	(0.001)	(0.003)
Age-cubed	1.000***	1.000***	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.842***	0.844***	0.846***	0.741**
	(0.025)	(0.047)	(0.033)	(0.107)
Non-white	1.022	1.203***	0.978	1.265***
	(0.020)	(0.040)	(0.027)	(0.102)
Years of education	1.032***	0.953***	1.027***	0.929***
	(0.003)	(0.004)	(0.004)	(0.009)
Married	1.462***	0.292***	1.656***	0.798
	(0.025)	(0.011)	(0.094)	(0.120)
Number of kids	0.848***	0.860***	0.834***	0.865***
	(0.004)	(0.005)	(0.005)	(0.013)
Employed	1.014	0.380***	1.029	0.389***
	(0.018)	(0.026)	(0.023)	(0.048)
Num. of observations	220,280	80,976	115,235	34,352

Note: The sample consists of parent-child dyads where the child is over 18 years old in HRS. Each column indicates each type of non-financial outcome, which is based on a separate logistic regression. Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. Standard errors are robust clustered on the parent (in parentheses). *** p<0.01 ** p<0.05 * p<0.1

Table 1.6. Association between co-residency and immigration status

	1. Immigrant-native category	2. Immigrant-mixed-native category
	(A) Co-residency	(B) Co-residency
Immigrant-native category (reference: native)		
Immigrant	1.298***	
	(0.033)	
Immigrant-mixed-native category (reference: native)		
Mixed status		0.993
		(0.047)
Immigrant		1.805***
		(0.085)
Child's characteristics		
Household income	0.722***	0.699***
	(0.006)	(0.009)
Age	0.637***	0.646***
	(0.020)	(0.027)
Age-squared	1.008***	1.007***
	(0.001)	(0.001)
Age-cubed	1.000***	1.000***
	(0.000)	(0.000)
Years of education	0.949***	0.922***
	(0.004)	(0.006)
Married	0.255***	0.190***
	(0.006)	(0.007)
Currently in school	1.371***	1.323***
	(0.039)	(0.049)
Number of kids	0.810***	0.749***
	(0.006)	(0.011)
Gender (Male)	1.043**	1.099***
	(0.018)	(0.028)
Employed	0.863***	0.821***
	(0.020)	(0.030)
Parent's characteristics (head of household)		
Household income	0.977***	0.974***
	(0.004)	(0.008)
Household wealth	0.997*	0.989***
	(0.002)	(0.003)
Age	1.134*	0.990
	(0.079)	(0.096)
Age-squared	0.998	1.001
	(0.001)	(0.001)
Age-cubed	1.000	1.000
	(0.000)	(0.000)
Hispanic	1.379***	1.339***
	(0.039)	(0.056)
Non-white	1.179***	1.178***
	(0.023)	(0.036)
Years of education	0.974***	0.975***
	(0.003)	(0.004)
Married	1.006	2.961***
	(0.019)	(0.244)
Number of kids	0.846***	0.836***
	(0.004)	(0.006)
Employed	1.088***	1.046
	(0.023)	(0.032)
Num. of observations	310,156	168,672

Note: The sample consists of parent-child dyads where the child is over 18 years old in HRS. Each column is based on a separate logistic regression. Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. Standard errors are robust clustered on the parent (in parentheses). *** p<0.01 ** p<0.05 * p<0.1

Table 1.7. Sensitivity check (1): Models (for financial transfer amount)

	1. Parent-to-child Financial Transfer Amount				2. Child-to-parent Financial Transfer Amount			
	(A) Two-part (amount>0,main)	(B) Two-part (raw amount)	(C) Heckman	(D) Tobit	(E) Two-part (amount>0, main)	(F) Two-part (raw amount)	(G) Heckman	(H) Tobit
Panel 1. Validity of assumption of the Two-part model								
Panel 1-1. Immigrant-native category (reference: native)								
Immigrant	4,883.39***	1,272.25***			703.02***	69.44***		
	(366.73)	(68.63)			(225.34)	(8.73)		
n	43,913	275,599			7,409	275,599		
Panel 1-2. Immigrant-mixed status-native category (reference: native)								
Mixed	6,632.40***	1,694.00***			101.44	14.53		
	(610.54)	(131.64)			(559.36)	(12.03)		
Immigrant	3,805.18***	1,179.29***			834.05*	112.17***		
	(686.69)	(135.50)			(449.43)	(12.38)		
n	27,764	150,875			2,481	150,875		
Panel 2. Model selection								
Panel 2-1. Immigrant-native category (reference: native)								
Immigrant	4,883.39***		6,930.61***	4,892.05***	703.02***		8,052.48	952.03***
	(366.73)		(732.44)	(290.04)	(225.34)		(5,074.44)	(168.17)
Inverse			68,881.27***				177.07	
Mills- ratio			(4,959.43)				(120.16)	
n	43,913		275,599	275,599	7,409		275,599	275,599
Panel 2-2. Immigrant-mixed status-native category (reference: native)								
Mixed	6,632.40***		6,510.53***	6,163.32***	101.44		2,343.35	148.26
	(610.54)		(1,196.61)	(479.04)	(559.36)		(2,866.30)	(392.32)
Immigrant	3,805.18***		2,623.64***	2,009.97***	834.05*		9,565.93	709.97**
	(686.69)		(534.80)	(533.16)	(449.43)		(10,528.46)	(342.99)
Inverse			75,287.40***				28,031.64	
Mills- ratio			(6,705.88)				(33,639.03)	
n	27,764		150,875	150,875	2,481		150,875	150,875

Note: All regressions include the same covariates as the baseline regressions reported in Table 1.2. Columns (A) and (E) show estimates from a two-part model with non-logged transfer amount conditional on positive values (Table 1.2 presents a baseline two-part model with logged transfer amount conditional on positive values). Columns (B) and (F) present estimates from a two-part model with an original transfer amount that includes zero values. Columns (C) and (G) present estimates from Heckman's two-stage models (The estimates are statistically significant if inverse Mills-ratios are statistically significant). Columns (D) and (H) show estimates from Tobit models. *n* is the sample size in each model. Robust standard errors clustered at parent-level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. *** p<0.01 ** p<0.05 * p<0.1

Table 1.8. Sensitivity check (2): Measures

	1. Financial Transfers				2. Non-financial transfers		3. Co-residency
	Parent-to-child		Child-to-parent		Parent-to-child	Child-to-parent	
	(A) Probability	(B) Amount	(C) Probability	(D) Amount	(E) Grandchild care	(F) Elder care	(G) Co-residency
Panel 1. Immigrant-native category (reference: native-born)							
Panel 1-1. Main results							
Immigrant	1.160***	0.139***	1.358***	0.199***	0.914***	1.117*	1.298***
	(0.028)	(0.020)	(0.056)	(0.043)	(0.027)	(0.069)	(0.033)
Panel 1-2. Hot-deck imputation income results							
Immigrant	1.153***	0.137***	1.323***	0.188***	0.911***	1.124*	1.276***
	(0.028)	(0.018)	(0.057)	(0.037)	(0.027)	(0.072)	(0.032)
Panel 1-3. Categorical income results							
Immigrant	1.151***	0.165***	1.324***	0.189***	0.911***	1.123*	1.272***
	(0.028)	(0.018)	(0.057)	(0.037)	(0.027)	(0.072)	(0.032)
n	275,599	43,913	275,599	7,409	213,438	77,594	310,156
Panel 2. Immigrant-mixed-native category (reference: native-born)							
Panel 2-1. Main results							
Mixed-status	1.030	0.122	1.000	0.072	0.898**	1.246***	0.993
	(0.038)	(0.129)	(0.100)	(0.103)	(0.043)	(0.096)	(0.047)
Immigrant	1.057**	0.205***	2.159***	0.293***	0.823***	1.350***	1.805***
	(0.030)	(0.037)	(0.191)	(0.080)	(0.037)	(0.098)	(0.085)
Panel 2-2. Hot-deck imputation income results							
Mixed-status	1.030	0.097	1.005	0.081	0.831**	1.296***	0.984
	(0.037)	(0.098)	(0.101)	(0.134)	(0.037)	(0.096)	(0.045)
Immigrant	1.056**	0.246***	2.110***	0.251***	0.894**	1.345***	1.768***
	(0.029)	(0.081)	(0.193)	(0.062)	(0.043)	(0.109)	(0.082)
Panel 2-3. Categorical income results							
Mixed-status	1.030	0.093	1.006	0.053	0.831**	1.192	0.975
	(0.037)	(0.098)	(0.101)	(0.087)	(0.037)	(0.246)	(0.045)
Immigrant	1.053**	0.241***	2.120***	0.279***	0.896**	1.353**	1.754***
	(0.028)	(0.081)	(0.194)	(0.084)	(0.043)	(0.199)	(0.082)
n	150,875	27,764	150,875	2,481	111,289	31,425	168,672

Note: All regressions include the same covariates as the baseline regressions reported in Table 1.2, except for the child's income. Each column indicates estimates for separate outcomes (and samples) in Tables 1.2 to 1.6. Panels 1-1 and 2-1 show estimates from the main model using income imputation of Haider and McGarry (2012). Panels 1-2 and 2-2 indicate estimates using hot-deck imputed income. Panels 1-3 and 2-3 present estimates using original categorical income in HRS data. *n* is the sample size in each model. Robust standard errors clustered at parent-level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. *** p<0.01 ** p<0.05 * p<0.1

Table 1.9. Relationship between financial transfers and poverty status of older parents

	1. Immigrant-native		2. Immigrant-mixed status-native		
	U.S-born (Native)	Foreign-born (Immigrant)	Native	Mixed-status	Immigrant
Panel 1. Economic resources					
Employed	32.53%	31.95%*	36.86%	35.40%*	34.76%*
Household income	63,196	61,340*	79,107	78,881*	71,014*
Household wealth	510,705	473,117*	634,428	610,414	529,522*
Household financial wealth	154,771	143,227*	182,456	171,275*	158,677*
Total income	32,221	31,753*	36,184	35,943*	35,967*
Earnings	13,976	13,113*	16,673	17,574*	12,399*
Social Security benefits	9,795	8,018*	9,182	8,277*	6,756*
Private pension income	5,560	3,729*	5,537	5,558	2,160*
n	74,881	10,438	49,040	3,812	3,675
Panel 2. Poverty status by transfer type					
Panel 2-1. Child-to-Parent transfer					
Experiencing Transfer	17.4%	30.6%*	10.6%	16.5%*	35.0%*
Not Experiencing Transfer	7.2%	16.0%*	3.7%	8.5%*	16.1%*
Difference	10.2%p	14.6%p	6.9%p	8.0%p	18.9%p
n	72,490	10,171	48,513	3,768	3,642
Panel 2-2. Parent-to-Child transfer					
Experiencing Transfer	3.8%	5.8%*	2.4%	3.9%*	6.7%*
Not Experiencing Transfer	9.6%	21.8%*	4.7%	11.3%*	21.9%*
Difference	-5.8%p	-16.0%p	-2.3%p	-7.4%p	-15.2%p
n	72,490	10,171	48,513	3,768	3,642
Panel 3. Poverty status with/without transfer					
With Transfer	17.4%	30.6%*	10.6%	16.5%*	35.0%*
Without Transfer	20.8%	37.9%*	11.7%	18.5%*	41.1%*
Difference	-3.4%p	-7.3%p	-1.1%p	-2.0%p	-6.1%p
n	19,835	2,755	13,061	1,217	894

Note: The sample consists of older parents whose child is over 18 years old in HRS and not living with the child from 2002 to 2018 years. Column 1 presents descriptive data for the immigrant-native sample and Column 2 for the immigrant-native-mixed sample limited to two-parent households. "Experiencing transfer" refers to poverty rates of older parents who receive child-to-parent transfer (Panel 2-1) or send parent-to-child- transfer (Panel 2-2); "Not Experiencing transfer" refers to poverty rates of those who do not receive child-to-parent transfer (Panel 2-1) or do not send parent-to-child transfer (Panel 2-2). The "Difference" in Panel 2 lists differences in poverty rates between "Experiencing transfer" and "Not Experiencing transfer" groups (= Exp – Not exp). In Panel 3, "With transfer" refers to poverty rates of older parents who receive transfer whereas "Without transfer" refers to poverty rates of older parents not considering transfers. The "Difference" in Panel 3 presents poverty rates differences between "With transfer" and "Without transfer" groups (= With - Without). *n* is the sample size in each model. The source is HRS data from 2002 to 2018 years. Asterisk (*) indicates that differences in mean values between immigrant and native (and immigrant-native and mixed status-native) are statistically significant with 99% confidence level ($p<0.01$.).

Appendix A1.1. Descriptive statistics: Sample with coresident family

	1.Immigrant-native category		2.Immigrant-mixed-native category		
	U.S-born (Native)	Foreign-born (Immigrant)	Native	Mixed status	Immigrant
Panel 1. Financial transfer (parent-to-child)					
Probability	20.7%	18.8%*	24.2%	24.7%*	17.6%*
Amount (>0)	9,763	13,477*	10,401	16,069*	12,927*
Average Amount (including zeros)	2,025	2,537*	2,517	3,963*	2,269*
Panel 2. Financial transfer (child-to-parent)					
Probability	2.5%	4.2%*	1.4%	1.8%*	5.1%*
Amount (>0)	3,709	3,775*	4,114	3,585	3,417*
Average Amount (including zeros)	93.0	157.1*	56.1	63.8*	174.7*
Panel 3. Non-financial transfers					
Grandchild care(parent-to-child)	19.1%	17.0%*	23.9%	19.9%*	20.1%*
Care of parents with IADL/ADL(child-to-parent)	11.1%	12.0%*	4.0%	5.3%*	7.5%*
Co-residency	11.7%	19.5%*	12.2%	17.0%*	25.1%*
Panel 4. Child's characteristics					
Median annual income	56,449	46,294*	58,889	51,948*	42,628*
Imputed annual income	50,383	43,665*	51,034	46,132*	40,485*
Categorical annual income					
- Less than $10,000	10.6%	17.7%*	10.0%	15.7%*	21.0%*
- $10,000 ~ $34,999	27.3%	29.3%*	26.8%	28.0%	29.8%*
- $35,000 ~ $69,999	52.4%	45.6%*	53.3%	47.8%*	43.3%*
- More than $70,000	9.7%	7.4%*	9.9%	8.5%*	5.9%*
Age	39.9	37.4*	37.5	35.9*	34.5*
Years of education	13.7	13.3*	14.0	13.9	13.2*
Married	57.1%	53.7%*	58.1%	51.1%*	55.5%*
Currently in school	7.9%	10.9%*	9.6%	13.1%*	12.4%*
Number of kids	1.6	1.5	1.5	1.2*	1.5
Gender (Male)	49.9%	49.6%	50.5%	50.0%*	48.8%*
Employed	81.2%	78.1%*	83.8%	80.1%*	77.5%*
Panel 5. Parent's characteristics (head of household)					
Total household annual income	77,332	74,688*	106,759	108,281*	94,100*
Total household wealth	535,390	483,848*	725,117	728,901*	522,481*
Age	67.8	67.0	66.1	65.7	65.2*
Years of education	12.6	10.6*	13.0	12.7*	9.9*
Married	53.8%	59.8%*			
Number of kids	4.0	4.3	4.0	4.2*	4.5*
Employed	42.0%	41.3%*	50.1%	49.8%*	47.9%*
Hispanic	4.3%	46.3%*	3.7%	25.8%*	58.7%*
Non-white	16.2%	31.4%*	10.7%	15.0%*	42.6%*
Number of observations	263,682	46,474	140,266	12,206	16,200

Note: The sample consists of parent-child dyads where the child is over 18 years old. Column (1) presents descriptive data for the immigrant-native sample and Column (2) for the immigrant-native-mixed sample limited to two-parent households. Data is sourced from HRS data from 1996 to 2018 years. Asterisk (*) indicates that differences in mean values between immigrant and native (and immigrant-native and mixed status-native) are statistically significant with 99% confidence level ($p<0.01$.)

Paper 2: Intergenerational transfers in immigrant and native families: Do life events matter?

1. Introduction

Financial support within families serves as informal insurance against life events (Laferrère & Wolff, 2006). For example, a child may cover a sick parent's medical expenses, and parents may send money to their child who has lost a job (Edwards, 2020; Wiemers, 2014). More than half of adults over age 50 sent or received intergenerational transfers once or twice in a 25-year period (See Appendix Figures A2.1 and A2.2). This relatively rare frequency suggests that transfers correspond to transitory life shocks rather than routine low-income status (McGarry, 2016). Some transfer donors might absorb these negative shocks and maintain their commitment to transfer recipients; others may respond by reducing transfers.[6] Simultaneously, donors may also increase their transfers corresponding to recipients' changing needs due to life events, or they may maintain their current level of support due to their own life events. Certain questions arise in this context: 1) How do economic and health events affect intergenerational transfer decisions?; and 2) Do these processes impact immigrant and native families differently?

These questions are important in terms of the redistribution effects of intergenerational transfers. If donors reduce transfers when faced with economic or health shocks, then transfers are not a reliable income source for vulnerable groups (e.g., retired parents, disabled relatives). State programs (e.g., Social Security, disability insurance) then constitute a more reliable safety net.

[6] A transfer "recipient" refers to an older parent in child-to-parent transfers or to an adult child in parent-to-child transfers and (intended) future transfer from parent to child. A transfer "donor" is an adult child in child-to-parent transfers or an older parent in parent-to-child transfers and (intended) future transfer from parent to child.

Similarly, if parent-to-child (or child-to-parent) transfers do not increase with adverse events in recipients' lives, intergenerational transfers cannot protect people from the vagaries of pandemics or other adverse events (Cherlin et al., 2013; Gottlieb et al., 2014).

Studies on the impacts of life events (shocks) on intergenerational transfers shows that these events significantly influence transfer decisions (McGarry, 2016; Schaller & Eck, 2021; Zissimopoulos et al., 2020). Scholars have investigated life events on either the donor side or the recipient side. Such studies could contain potential omitted variable bias because donor- and recipient-related factors both affect transfer decisions (Laferrère & Wolff, 2006; Laitner, 1997).

There is much less research on how economic and health shocks impact intergenerational transfers in immigrant families, who previous research suggests have been more vulnerable during business cycles or public health crises (Gill & Shaeye, 2022; Kpodar et al., 2022; Orrenius & Zavodny, 2010). Preliminary research (in Paper 1) also shows that despite their lower incomes and wealth (compared to the U.S.-born older adults), intergenerational transfers are substantially larger between immigrant parents and their children. Yet there is little research on how immigrants respond to economic and health shocks in their lives and those of the recipients. Throughout this chapter, I use parent-to-child transfers to denote transfers from parents to children and child-to-parent transfers to denote transfers from children to parents.

The current study contributes to the existing literature in two ways. First, the study is the first to examine how and to what extent immigrants and native-born citizens respond differently to life events while providing transfers to parents or children. No study to my knowledge has explored this issue, which is particularly relevant today in light of macro events such as the Great

Recession and the recent COVID-19 pandemic.[7] Second, donors' and recipients' life events are explored simultaneously to mitigate potential omitted variable bias in prior studies. Findings from this study reveal whether donors adapt transfers to their own or recipients' life events and whether these adjustments vary between immigrants and natives.

2. Literature Review

Theoretical considerations

Altonji et al.'s (1997, 2007) altruism model specifies how life events inform transfer decisions.[8] Amid uncertainty about permanent income, a donor may be incentivized to delay transfers until gaining more information (e.g., Davies, 1981), but recipients' potential liquidity constraints might counteract this behavior (McGarry, 2016). A recipient's life events can lead a donor to reconsider the recipient's needs given these possible constraints (Altonji et al., 1997, 2007). Donors' life events (e.g., hospitalization) are also associated with their financial stability and (future) income stream, thus affecting transfer decisions (Cox, 1990). Empirical investigations should account for these events among donors and recipients to determine whether suggested theoretical pathways are evidenced in this context.

Two competing hypotheses ground inferences about the immigrant–native differences in life event–related transfer decisions. Under the solidarity hypothesis, immigrant families'

[7] Exclusively for the immigrant group, prior studies have investigated their transfers decisions at the country level. For example, immigrants' transfers to their home countries (i.e., remittance) often increase significantly amid local macroeconomic shocks of home countries such as natural disasters (Yang & Choi, 2007), economic recessions (Barajas et al., 2010; De et al., 2019; Frankel, 2011), and the COVID-19 pandemic (Kpodar et al., 2022). Immigrants' transfer decisions are associated with negative macroeconomic events (i.e., economic recessions, COVID-19), which can be further tied to individual life events (e.g., job loss, health shock) in this study.

[8] The altruism models generally predict that transfer decision is positively associated with transfer donor's income (e.g., financial availability) and negatively associated with transfer recipient's income (e.g., need for resources) (Cox & Jappelli, 1990; McGarry & Schoeni, 1995; Schoeni, 1997).

intergenerational support can lead to more sensitive responses to life events based on cultural and social norms (McDonald, 2011; Nauck, 2001). The conflict hypothesis asserts that immigrants show less responsive intergenerational support due to intercultural and intergenerational conflicts (Merz et al., 2009).

Empirical evidence

Several U.S. studies have examined the effects of life events on intergenerational financial transfers (see for example, McGarry, 2016; Schaller & Eck, 2021; Zissimopoulos et al., 2020), but they have focused on the life events of either a donor or a recipient. For instance, McGarry (2016) investigated the impacts of events in the lives of adult children (recipients) on financial transfers from parents to children using the Health and Retirement Study (HRS) data between 1992 and 2008. Child- and family-level fixed effects models were used to estimate the likelihood and amount of parental transfer to adult children. McGarry (2016) found events such as child job loss or divorce are strong predictors of parent-to-child transfers. In contrast, Zissimopoulos et al. (2020) focused primarily on donors' life events. They estimated the impact of changes in parental income and wealth loss during the Great Recession in 2008 on changes in parental financial transfers to their children analyzing the Panel Study of Income Dynamics (PSID) from 2005 to 2011. They found that income loss had a small negative effect on parent-to-child transfers, while wealth loss did not significantly affect the transfer decisions.

Schaller and Eck (2021) estimated how parent-to-child and child-to-parent transfers are shaped by events in the lives of parents, but they did not address events in the lives of children. The events they studied were: job exit, wealth loss, widowhood, and health shocks of parents.

Using HRS data between 1994 and 2014, results revealed sharp declines in parental transfers to children after negative shocks to parents' wealth, income, and health. Other adverse life events presented similar but more mild estimates.

Empirical evidence on how life events impact transfer decisions is inconclusive. For instance, while recipients' wealth loss leads to an increase in transfers in Schaller & Eck (2021), it is not significant in McGarry (2016). Such inconsistency could arise from omitting life events in the lives of recipients/donors. These events are likely to concurrently happen during life- and business-cycle (e.g., the death of a grandparent and birth of a grandkid, parent and child's job loss during the recession). In this study, a non-negligible portion of observations (i.e., 12.97%) experienced life events of a parent and a child at the same time. A substantial portion of unique individuals (i.e., 43.23%) also simultaneously experienced both parties' events at least once during survey periods.

3. Data and Sample

This study uses data from twelve survey waves based on original public-use HRS files merged with the RAND version of HRS imputation files between 1996 and 2018. In this paper, I specifically refer to panel aspects of the HRS dataset to analyze the life events of respondents (older parents) and their children. HRS provides details on demography, employment, health status, family and social relationships, and financial transfers of respondents and their children. This information is used to define the life events of transfer donors and recipients.

The sample consists of a parent–child dyad in a non-coresident family (e.g., parents and their children who do not live with the parents). This sample restriction can address potential biases

from transfers of coresident families (e.g., shared living cost vs. financial transfer). The final analytic sample includes 24,921 unique parent–child dyads, and a total of 150,474 recode-period observations during the sample periods.

4. Measures

Outcomes

I investigate financial transfers from older parents to their adult children (parent-to-child transfer) and from adult children to their older parents (child-to-parent transfer). In the HRS, respondents are asked to report how much money they or their spouse has received from their child and how much they have given to their child in the last two years; the amounts are measured as the total amount in U.S. dollars. I study four outcome variables: the likelihood of parent-to-child financial transfer, the likelihood of child-to-parent financial transfer, (logged) amount of parent-to-child financial transfer, and (logged) amount of child-to-parent financial transfer. The amounts of transfers are CPI-adjusted based on the 2018-year value.

The HRS measures the expected probability of leaving financial resources to one's child in the future ranging from 0 to 1. This metric helps to capture how current and intended (future) transfers vary in response to life events. Therefore, additionally, I study expectations about future financial transfers as an outcome variable.

Predictors

The current study stratifies families according to the nativity composition of the parent's household (the same as those in Paper 1) in three groups: both parents U.S.-born (native); both parents foreign-born (immigrant); and one parent foreign-born and one parent U.S.-born (mixed-status). The sample is accordingly restricted to two-parent (couple) households because mixed-status families could not be identified in households with only a single-parent.

The primary variables of interest in this study are life events commonly experienced by adult children and their older parents. I construct these variables generally based on definitions in McGarry (2016) and Schaller and Eck (2021). A dichotomous variable indicates 1 if a parent (or child) did not experience an event in the previous wave (*t-1*) but has experienced it in the current wave (*t*), similar to prior work (Dobkin et al., 2018).

Events in children's lives include milestones such as college graduation, marriage, childbirth, and social and economic shocks: divorce, and job loss (McGarry, 2016). College graduation is a dummy variable denoting whether the child reports more than 16 years of schooling in the current wave versus the last wave. Job loss is a dummy variable denoting whether a child is unemployed in the current wave but employed in the last wave. Marriage, divorce, and childbirth respectively denote whether the child is married, divorced, or has had a new child in the current wave versus the last wave.

Parents' events include widowhood, loss of job and wealth, and three health shocks (i.e., hospitalization, disability, and poor health) (Schaller & Eck, 2021). Widowhood is a dichotomous variable denoting whether a parent was married in the last wave but is widowed in the current wave. Job loss is a dummy variable denoting whether at least one parent worked for pay in the last wave but not in the current wave. Wealth loss is a dummy variable indicating whether households with at least $20,000 of net wealth lost more than 25% of this amount over the last wave, following

Schaller and Eck (2021). Hospitalization and disability are dichotomous variables respectively denoting if a parent reports hospitalization and difficulty with activities of daily living (ADLs) (or instrumental ADLs) in the current wave versus the previous wave.

Prior studies used self-reported health status to measure a poor health status (i.e., Schaller & Eck, 2021): a dummy variable denoting whether a parent has reported a poor (subjective) health condition in the current wave versus the last wave (based on a scale anchored by 1 = *excellent*, 5 = *poor* in the HRS). The self-reported health measure in the HRS is subjective and may be correlated with other life events, and could lead to potential biases, as pointed out by Bound et al. (1999) and Insler (2014).[9] To address such potential biases, I use a predicted probability of poor health status that utilizes less subjective information (e.g., doctor-diagnosed health conditions) in the robustness check section. Other control variables are the same as those in Paper 1.

5. Analytic Strategy

As done in studies regarding how life events influence transfers, I adopt a two-way fixed effects model to control for unobserved time-invariant individual heterogeneity. This approach is appropriate because transfer decisions can be based on donors' perceptions of recipients' situations (e.g., how a parent views their child's abilities) (McGarry, 2000). Transfers can therefore reflect recipients' characteristics (i.e., industriousness or ability). These donors' perceptions and recipients' attributes are likely unobservable. To account for these factors, I control for parent- and

[9] Prior studies suggested that self-reported health status can be vulnerable to potential biases (Bound, 1991; Insler, 2014; Waidmann et al., 1995). One bias, known as the justification bias, occurs when older adults overstate their poor health conditions to justify their retirement or job changes (Bazzoli, 1985; Bound, 1991; McGarry, 2004). Another bias, known as the role bias, occurs when retirees feel healthier than before because their roles are less physically (or mentally) demanding, leading to self-reported health exaggeration without actual improvements in health (Insler, 2014; Neuman, 2008).

child-fixed effects in the final model. Parent-to-child transfers are considered first using the following regression equations:

$$Y_{ict} = \alpha + \beta_1 \left(EventP_{it} * I_i \right) + \beta_2 I_i + \varphi P_{it} + \gamma C_{ct} + \mu_t + \varepsilon_{ict} \quad (1)$$

$$Y^1{}_{ict} = \alpha^1 + \beta^1{}_1 (EventP_{it} * I_i) + \varphi^1 P_{it} + \gamma^1 C_{ct} + \mu^1{}_t + \lambda_i + \varepsilon^1{}_{ict} \quad (2)$$

$$Y^2{}_{ict} = \alpha^2 + \beta^2{}_1 (EventP_{it} * I_i) + \beta^2{}_2 (EventC_{ct} * I_i) + \varphi^2 P_{it} + \gamma^2 C_{ct} + \mu^2{}_t + \delta_c + \varepsilon^2{}_{ict} \quad (3)$$

where Y_{ict} denotes the likelihood (or (logged) amount) of financial transfers from a parent (i) to a child (c) at wave (t).[10] The coefficients of interest are β_1, $\beta^1{}_1$, $\beta^2{}_1$ and $\beta^2{}_2$, which denote differences in transfers between immigrant (or mixed-status families) and native-born individuals corresponding to life events. *Event* is a set of dummy variables for life events of a child ($EventC_{ct}$) or a parent ($EventP_{it}$). I_i is a vector of dummy variables indicating three groups: an immigrant family (both parents are foreign-born), a mixed-status family (one parent is foreign-born and one parent U.S. born), and native parents (both parents born in the U.S.) which are a reference group. μ_t denotes a time (wave) fixed effect. λ_i and δ_c respectively denote family and child fixed effects. The fixed effects control for time-invariant unobserved heterogeneity of a family and a child, which is associated with transfer decisions. P_{it} denotes the head of parent household's characteristics: age, educational status, number of children, marital status, employment status, race and ethnicity, and household income and wealth. C_{ct} denotes a child's characteristics: age, gender, educational status, number of children, marital status, employment status, and household income.

[10] For dichotomous outcomes (i.e., transfer likelihood), a linear probability model is used for main analyses. Estimates based on a logistic regression model present similar trends with those in the main analyses.

Robust standard errors are clustered on the family level and analyses are weighted using HRS household weights.

Three models are estimated in the main analysis. Model 1 (Equation [1]) is estimated by an ordinary least squares (OLS) regression that includes immigrant status (I_i), life events of a parent ($EventP_{it}$), and other characteristics (P_{it}, C_{ct}, μ_t), but excludes family- and child-fixed effects. This specification provides a brief description of transfer behavior and a benchmark for comparing subsequent models. Model 2 (Equation [2]) additionally includes a family-fixed effect (λ_i) to control for unobserved heterogeneity of transfer donor (parent).[11] The family-fixed effect control changes in the events within the lives of a parent controlling for unobservable time-invariant characteristics of the parent (e.g., subjective perceptions of children's industriousness). Finally, Model 3 (Equation [3]) adds transfer recipient-side factors: the life events of a child ($EventC_{ct}$) and a child-fixed effect (δ_c). The child-fixed effect control changes unobserved aspects of a child (i.e., children's industriousness or capability). The family-fixed effect gets dropped from Model 3 due to the child-fixed effect.

Next, I analyze child-to-parent transfers using models in Equations [4] to [6]. I use subscript (c) to distinguish coefficients from Equations [1] to [3]. In this analysis, $Y_{(c)ict}$ denotes the likelihood (or (logged) amount) of financial transfers from a child (c) to a parent (i) at wave (t). Definitions of all other variables are identical to those in Equations [1] to [3]. Three models are also used in child-to-parent transfers, similar to parent-to-child transfers. Model 1 (Equation [4]) is an ordinary least squares (OLS) regression that include life events of donor (child) and other covariates but excludes family and child fixed effects. Model 2 (Equation [5]) additionally includes

[11] Due to the family- and child-fixed effects, immigration status (I_i) and covariates (e.g., race and ethnicity, gender) gets dropped from Models 2 and 3.

a donor (child) fixed effect, similar to parent-to-child transfers. Model 3 (Equation [6]) adds a recipient-side factor: the life events of a parent. The family-fixed effect is dropped from Model 3.

$$Y_{(c)ict} = \alpha_{(c)} + \beta_{(c)1}\,(EventC_{ct} * I_i) + \beta_{(c)2} I_i + \varphi_{(c)} P_{it} + \gamma_{(c)} C_{ct} + \mu_{(c)t} + \varepsilon_{(c)ict} \quad (4)$$

$$Y^1{}_{(c)ict} = \alpha^1{}_{(c)} + \beta^1{}_{(c)1}(EventC_{ct} * I_i) + \varphi^1{}_{(c)} P_{it} + \gamma^1{}_{(c)} C_{ct} + \mu^1{}_{(c)t} + \delta_{(c)c} + \varepsilon^1{}_{(c)ict} \quad (5)$$

$$Y^2{}_{(c)ict} = \alpha^2{}_{(c)} + \beta^2{}_{(c)1}(EventC_{ct} * I_i) + \beta^2{}_{(c)2}(EventP_{it} * I_i) + \varphi^2{}_{(c)} P_{it} + \gamma^2{}_{(c)} C_{ct} + \mu^2{}_{(c)t} + \delta^2{}_{(c)c} + \varepsilon^2{}_{(c)ict} \quad (6)$$

6. Descriptive statistics

Table 2.1 shows that a fair proportion of respondents reported life events that might have affected parent-to-child or child-to-parent transfers. Immigrants (56.8%) and mixed-status (56.2%) families experience more parental events than native families (55.9%) (Panel 1). Likewise, immigrants (25.8%) and mixed-status (26.5%) families are more exposed to any type of children's life events than native families (24.4%) (Panel 2). In Panel 3, immigrants are more involved with child-to-parent transfers compared with native (and mixed-status) families as mentioned in Paper 1. Conversely, immigrants are less involved in parent-to-child transfers than native (and mixed-status) families despite children's life events being more common than for natives. The total amounts of parent-to-child and child-to-parent transfer follow these trends, but the net amounts (excluding the effect of transfer probabilities) show an inconsistent trend across groups (Panel 4). The immigrant group has the lowest future (parent-to-child) expected probability in Panel 5, similar to the case of current parent-to-child transfer probability in Panel 3.

Table 2.2 contextualizes the relationships between transfers and various life events by comparing transfer probabilities between individuals who do and those who do not experience life events. Across all groups, events in the lives of transfer recipients (donors) are generally positively (negatively) correlated with differences in transfer probability between those who experience an event and those who do not. Specifically, the likelihood of parent-to-child transfer is higher for those who experience any recipient (i.e., child) life event (Panel 1, Column A) but lower for those who experience any donor (i.e., parent) life event (Panel 2, Column A). The same patterns apply to child-to-parent transfer (Column B) and future (parent-child) transfer probabilities (Column C).

Furthermore, differences between people who do and do not experience life events are larger for mixed-status and immigrant families than for native families. As an example, these statistically significant differences in parent-to-child transfer probabilities are 5 percentage points for natives but 5.9 percentage points for mixed-status and 5.8 percentage points for immigrants (Panel 1, Column A). These trends also emerge for child-to-parent and future (parent-to-child) transfers. Given these descriptive results, immigrant and mixed-status families' intergenerational transfers seem particularly responsive to life events relative to native families.

These cross-sectional descriptive comparisons, however, do not include controls for sociodemographic factors (as also analyzed in Paper 1) or for unobserved characteristics that affect transfer decisions such as a transfer recipient's ability or a donor's generosity (McGarry, 2016). Additionally, 43.23% of unique individuals in the sample of this study simultaneously experience both parent and child life events at least once during survey periods. I thus control for both parties' life events and (unobservable) characteristics in the regression analyses presented below.

7. Results

1) Preliminary analysis: Effects of life events on transfers

Before assessing how transfers' responsiveness to life events varied by immigration status, I evaluate whether life events influence transfer behaviors using an ordinary least squares (OLS) model without fixed effects. Table 2.3 displays results for donors' life events (Model 1) to which recipients' life events are then added (Model 2). There are three main preliminary findings. First, immigrants are more involved than natives in all transfers across all models. This trend echoes the conclusions from Paper 1; the current analysis additionally controls for life events. The mixed-status group also demonstrates a higher transfer probability and amount (except for child-to-parent transfers) than natives. These differences are relatively modest compared with those of the immigrant group.

Second, the effects of donors' life events on transfer decisions remain robust in models that control for recipients' life events, indicating that potential bias from omitting life events is unlikely to be a critical concern in this analysis. Upon controlling for recipient-side life events (from Model 1 to Model 2), a significant relationship persists between donor-side life events and transfer decisions, with a similar effect size. For parent-to-child transfers, the coefficients of parental life events remain nearly identical when including children's life events (Columns 2 and 4). Relatedly, for child-to-parent transfers, the coefficients of children's life events do not change significantly after integrating parental life events (Columns 6 and 8).

Finally, donors respond to recipients' needs associated with life events while the donors generally absorb shocks from their own life events and maintain their transfer commitment to recipients. That is, recipients' life events are more significantly related to transfer decisions

compared with donors' life events. For instance, parent-to-child transfer probability is positively associated with most recipients' (i.e., children's) life events but with few donors' life events (Column 2). In terms of child-to-parent transfer probability, no events for donors (i.e., children) are statistically significant except for children's job loss while a few recipient events (i.e., parental disability, poor health, job loss) are influential (Column 6). Recipients' life events therefore play a significant part in transfer decisions despite not being fully addressed in earlier work (e.g., Schaller & Eck, 2021; Zissimopoulos et al., 2020). The ensuing main analyses consider how and to what extent these findings vary by immigrant status after controlling for remaining sources of bias (e.g., unobserved characteristics).

2) Immigrant–mixed–native differences in the effects of life events on transfers

Table 2.4 shows that transfers' responsiveness to life events varies with immigration status. [12] As described in prior equations, Model 1 provides the base model against models that control for unobserved heterogeneity in donors' (Model 2) and recipients' characteristics (Model 3).

Parent-to-child transfers

Model 1 reveals significant differences in transfer decisions among immigrant, mixed–status and native families in response to life events of donor (parent) (Columns 1 and 4). When a parent experience a life event (e.g., hospitalization, subjective poor health, wealth loss), immigrant and mixed-status parents are more apt than their native counterparts to transfer to their children.

[12] I interpret the estimated results when a combined coefficient of a specific "event" and "the event * Immigrant (or Mixed)" is statistically significant at the 95% confidence level. For example, in Column 1, the combined coefficient of "Job loss" and "Job loss * Mixed" is statistically significant at the 95% confidence level.

Notably, parental job loss leads immigrant and mixed-status parents to transfer less than comparable natives in both likelihood and amount.

However, once controlling for donor (parent) fixed effects in Model 2, these differences among immigrant–mixed–native families mostly disappear, with the exception of the event relating to parental job loss (Columns 2 and 5). In the latter case, the discrepancies in transfer likelihood and amount are not eliminated but are considerably reduced. These results imply a possible relationship between transfer decisions and unobserved donor characteristics (i.e., parental generosity).

After controlling for recipient (child)-side factors in Model 3 to check omitted variable biases, the differences in transfer responsiveness remain the same as those in Model 2; a donor's job loss is the sole significant predictor of transfer differences (Panel 2, Columns 3 and 6). When a parent experiences a job loss, immigrant (and mixed-status) parents are 2.2% (and 2%) points less likely to send transfers compared with native counterparts—nearly identical to the proportions in Model 2. The transfer amounts also mirror trends in Model 2, with immigrant (and mixed-status) families transferring approximately 26% (25%) points less amount than comparable natives after parental job loss. These relatively consistent coefficients of parental life events across Models 2 and 3 convey that donors' and recipients' events are independently associated with parent-to-child transfers, as indicated in the preliminary analysis. Omitting one side of life events may not critically bias estimates.

Compared with donors' events, a relatively large number of life events among recipients (children) significantly affect transfer probability and corresponding differences (Panel 3, Column 3). For instance, children's divorce, graduation, marriage, and job loss are positively associated with transfer probability, echoing McGarry's (2016) findings. Among these events, children's job

loss and marriage are significantly associated with differences in parent-to-child transfer probability. Specifically, parents in mixed-status and immigrant families are 3.5% and 3.8% points more inclined to send parent-to-child transfer respectively in response to their child's job loss than comparable natives, namely due to recipients' higher probability of facing liquidity constraints. Upon their child's marriage, parents in mixed-status families are 2.7% points less likely to transfer than comparable natives; marriage lessens the likelihood of liquidity constraints because one's spouse can presumably help smooth negative (income) shocks.

Overall, immigrant and mixed-status parents' transfer decisions appear more responsive to child (recipient)'s changing circumstances (e.g., job loss, marriage) than the decisions of comparable natives. On the other hand, parent (donor)'s events are not much associated with transfers and corresponding differences in transfers, with the exception of parental job loss. Parent (donor) generally tend to hold parent-to-child transfers by absorbing negative shocks from their own life events as contrasted to the child (recipient)'s life events.

Child-to-parent transfers

Child-to-parent transfers change similarly to parent-to-child transfers across Models 1–3. The OLS estimates indicate that donors' family composition–related events (e.g., childbirth, divorce) and job loss influence differences in child-to-parent transfers among immigrant–mixed–native families (Columns 7 and 10, Panel 3). However, the differences typically diminish or disappear after controlling for unobserved donor (i.e., child) characteristics in Model 2. Differences in transfer probability derived from childbirth (for mixed-status) and job loss (for immigrants) each decline by approximately 20% (Column 8, Panel 3). Differences in transfer

amounts from job loss (for mixed-status) also fall (Column 11, Panel 3). All other differences in child-to-parent transfers become statistically insignificant at the 95% confidence level in Model 2. As in the case of parent-to-child transfers, child-to-parent transfers are significantly associated with unobserved donor characteristics (e.g., child's expectations or generosity).

These differences among immigration status toward donor' (child's) life events remain almost identical in Models 2 and 3 when including recipient- (parent-) side factors in Model 3 (Columns 9 and 12, Panel 3). Children in mixed-status families are 1.4% points less likely to financially support their parents than comparable natives in response to childbirth. Immigrants' children are 2.9% points less apt to transfer money than native counterparts when they lose jobs, with a negligible (i.e., 0.1 percentage point) difference from Model 2. Children in mixed-status families who experience job loss still transfer less amount than comparable native children, albeit with approximately a mere 1 percent point difference from Model 2. The fairly consistent estimates for differences in child-to-parent transfers toward child's life events convey the independent effects of donor and recipient events on these differences.

Similar to parent-to-child transfers, recipients' (i.e., parents') life events appear to affect child-to-parent transfers. Parental disability and job loss each amplify child-to-parent transfer probability; these events are closely tied to liquidity constraints, especially for older parents over age 50. Mixed-status (immigrant) children are accordingly 1.5% (1.4%) points more likely to send transfers to parents facing disability (job loss) than comparable natives. In transfer amount, children from mixed-status families also send approximately 13.2% points more amount money to their parents than comparable natives in response to parental disability.

In sum, children in immigrant and mixed-status families transfer more actively based on recipients' events (e.g., parental job loss, disability) than comparable natives. These children are

less likely to absorb shocks from their own life events (e.g., childbirth, job loss) than comparable natives, thereby reducing financial commitment to their parents. Job loss is again identified as a consistent predictor of the immigrant–native (mixed–native) differences in child-to-parent transfers, irrespective of transfer direction (parent-to-child vs. child-to-parent).

Intentions toward parent-to-child transfer in future

Comparing expectations about future transfer with current transfer probabilities can provide insight into Altonji et al. (1997)'s altruism model of how life events influence transfer decisions. In Columns 13 to 15 of Table 2.4, changes in estimates across Models 1–3 exhibit the same patterns as parent-to-child transfers. In Model 1, a substantial number of donor (parent) events are associated with immigrant–native (mixed status–native) differences in expectations about future transfers (Column 13). These differences in future transfers' responsiveness to life events mostly disappear in Model 2 with the exception of job loss, as in the case of parent-to-child transfers (Column 14). After controlling for recipient (child)-side factors in Model 3, the differences remain similar to those in Model 2 (Column 15). Specifically, in response to parental job loss, immigrant (mixed-status) parents are 3.3 (2.2) percentage points less likely to conduct future transfers than comparable natives. Once again, unobserved donor characteristics are significantly associated with future transfers (from Models 1 to 2), and life events of both the donor and the recipient independently influence transfer-related differences (from Models 2 to 3).

Notably, expectations about future (parent-to-child) transfer less reflect recipients' life events than current parent-to-child transfer probability. The life events of recipients (children) are not significantly associated with future transfer probability and related immigrant–mixed–native

transfer differences (Column 15, Panel 3). However, these events are highly significant predictors of parent-to-child transfers and corresponding differences (Column 3, Panel 3). On the other hand, donors' life events (e.g., parental job loss) consistently predict both future and parent-to-child transfer probabilities and differences therein (Columns 3 and 15, Panel 2).

These discrepant findings across future transfer and current parent-to-child transfer probabilities substantiate the theoretical model of Altonji et al. (1997, 2007) concerning the effects of life events on transfers. Results suggest that donors may delay transfer decisions due to uncertainty (e.g., Davies, 1981), which can be offset by the recipient's potential to encounter liquidity constraints. Recipients' current life events might signal such liquidity constraints and in turn influence current parent-to-child transfers. However, these events do not necessarily guarantee that the constraints will persist in the future and thus may not significantly affect future transfers.

8. Robustness checks

To test findings' validity, I conduct three robustness checks focusing on the measurement approach, outcome, and sample in Table 2.5. I first evaluate potential bias introduced by measurement error using the predicted probability of poor health status (instead of self-reported poor health status from HRS data). Following Bound et al.'s method (1999), this study regresses a dichotomous variable for self-reported poor health on related variables such as doctor-diagnosed chronic diseases, obesity, and other covariates, to get a predicted probability of poor health status.[13] The coefficients on poor health based on predicted poor health status (Model 2) have effect sizes

[13] Chronic diseases consist of doctor-diagnosed diseases such as diabetes, high blood pressure, lung diseases, cancer, heart problems, and stroke. Obesity is defined as a BMI over 30. Control variables include age, Hispanic origin/race/foreign-born, educational level and marital status. A linear probability model is used.

similar to those based on self-reported health status (Main Model). The size and significance of other covariates' coefficients are also similar to those of the main model; differences in coefficients' magnitude are also generally within 10% at most. The measurement of self-reported health status therefore does not significantly confound the main estimates in this case.

Second, I check whether sample attrition from the death of an older parent bias the main results. Prior studies have established a significant association between mortality and income (e.g., transfer income) (Chetty et al., 2016; Fitzpatrick & Moore, 2018). Results also can be overestimated if life events (e.g., parental health shocks) simultaneously affect death and transfers (or bequests) around the end-of-life period.[14] A sizable proportion of this sample (i.e., 38.9%) experience the death of an older parent during the 20-year study period, with the event accounting for 89.9% of sample attrition. To circumvent this potential bias, I limit the sample to individuals who do not experience older parental death. Estimated results from Model 3 indicate that the coefficients' significance and direction mirror the main results despite a substantial decrease in sample size. As such, the attrition from the death of an older parent does not seem to substantially bias main estimates, at least in this study.

Finally, I analyze whether transfer outcomes in *t-1* are impacted by current life events (*t*) to test the theoretical pathway of Altonji et al. (1997, 2007). [15] If a current transfer decision (*t*) is determined by concurrent life events that counter donors' incentives to delay transfers (e.g., Altonji et al., 1997, 2007), then these events should have lesser or no impacts on transfer decisions one wave earlier (*t-1*). The effect sizes and significance of findings under Model 4 are dissimilar to the main estimates in Main Model. Additionally, most coefficients in Model 4 are statistically

[14] The HRS questionnaire does not separate inter-vivo transfer from bequests around the end-of-life period.
[15] Because the impact of life events can continue one wave later (*t+1*), I analyze leaded outcomes (*t-1*) instead of lagged outcomes (*t+1*) to check robustness of my analyses.

insignificant. This further reaffirms the theoretical model of Altonji et al. (1997, 2007) underlying this study, in line with results from the future transfer analysis.

9. Discussion and Conclusion

This paper investigates the impacts of life events on intergenerational transfers and corresponding immigrant–native differences. Preliminary analyses reveal that the effects of donors' life events on transfer decisions are highly independent of the effects of recipients' life events on these decisions; omitting recipients' life events on one side does not critically confound estimates of donors' life events. Generally, recipients' life events are more strongly related to transfer probability and amounts than donors' life events in both parent-to-child and child-to-parent transfers.

With respect to immigrant–versus–native differences in transfer decisions, parent-to-child transfer decisions among immigrant and mixed-status parents are more influenced by children's changing circumstances (e.g., job loss and marriage) compared to native parents. However, older parents across the three groups similarly absorb shocks from their own life events apart from parental job loss. In child-to-parent transfers, children in immigrant and mixed-status families transfer more based on recipients' needs (e.g., parental job loss, disability) than comparable natives. Yet these children also reduce their financial commitment versus comparable natives in response to their own life events (e.g., childbirth, job loss). Future transfer probability is less reflective of recipients' (children's) life events than current parent-to-child transfer probability, consistent with Altonji et al.'s (1997, 2007) model stressing the roles of life events (related to liquidity constraints)

in transfer decisions. The results of robustness checks largely align with those in the main analyses: potential biases from measures, sample attrition, and transfer timing are not critically evident.

Overall, the findings in this study highlight two distinctive themes. First, discrepant results across models accentuate the importance of considering donor- and recipient-side factors when examining relationships between life events and transfers. Unobserved individual (donor) characteristics significantly confound estimates of transfer decisions in this study, as McGarry (2016) also noted. In addition, although omitting recipients' life events do not critically bias estimates on donors' life events, a relatively larger number of life events among recipients seems to be associated with parent-to-child and child-to-parent transfers.

Second, among several life events, job loss is a consistent predictor of differences in immigrant–versus–native transfer decisions after controlling for income and other factors. In response to transfer donors' job loss, immigrant and mixed-status families' transfer probability and amounts decline more than for their native counterparts. These results suggest that immigrant and mixed-status families have less cushion to manage adverse life events which affects their ability to support family members.[16] Further, immigrant and mixed-status families are also more likely than natives to send transfers in response to recipients' job loss.[17] Immigrant (and mixed-status) families' transfer decisions are thus more responsive to negative shocks from job loss than comparable natives, partially lending support to the solidarity hypothesis (McDonald, 2011; Nauck, 2001).

[16] Immigrants in the United States are more likely to work in temporary and part-time work than natives. Their unemployment rate also increases more than that of natives during economic recessions (Gill & Shaeye, 2022; Orrenius & Zavodny, 2010).
[17] The findings are also partly consistent with the prediction of the altruism model. As noted earlier, this model suggests a positive relationship between donors' economic resources (e.g., parental job loss in parent-to-child transfer) and transfers, and a negative relationship between recipients' economic resources (e.g., child's job loss in parent-to-child transfer) and transfers (Cox & Jappelli, 1990; McGarry & Schoeni, 1995; Schoeni, 1997).

Table 2.1. Descriptive statistics by immigration status

	(A) Native (U.S.-born) family	(B) Mixed-status family	(C) Immigrant family
Panel 1. Parent's life events			
Hospitalization	24.9%	26.9%*	25.8%*
Disability	16.1%	15.8%*	19.1%*
Poor health	7.3%	8.0%*	9.3%*
Widowhood	0.1%	0.1%	0.1%
Wealth loss	18.8%	19.1%*	17.4%*
Job loss	13.3%	13.6%*	14.0%*
Any events	55.9%	56.2%*	56.8%*
Panel 2. Child's life events			
Divorce	2.9%	2.7%*	2.5%*
Job loss	5.0%	5.3%*	5.7%*
Graduation	1.6%	2.2%*	1.8%*
Marriage	5.9%	6.9%*	6.6%*
Childbirth	12.9%	13.4%*	13.7%*
Any events	24.4%	26.5%*	25.8%*
Panel 3. Transfer probability			
Probability (Parent-to-child transfer)	21.9%	22.2%*	15.3%*
Probability (Child-to-parent transfer)	1.2%	1.5%*	4.4%*
Panel 4. Transfer amount			
Total amount (Parent-to-child transfer)	2,078	3,001*	1,983*
Total amount (Child-to-parent transfer)	49.24	45.48*	152.44*
Net amount (>0, Parent-to-child transfer)	9,508	16,422*	12,991*
Net amount (>0, Child-to-parent transfer)	4,122	2,966*	3,470*
Panel 5. Future Transfer			
Probability (Future parent-to-child transfer)	6.2%	6.1%	4.4%*
Number of observations	127,706	10,424	12,344

Note: The sample consists of parent-child dyads where the child is over 18 years old and not living with the parent in HRS. Column (A) shows descriptive data for the U.S.-born (native) sample, Column (B) for mixed-status families, and Column (C) for immigrant families. The numbers in each column represent the mean value for transfer probabilities and amounts. Data is sourced from HRS data from 1996 to 2018 years. Asterisk (*) indicates that differences in mean values between immigrant and native (mixed and native) are statistically significant with 99% confidence level ($p<0.01$.)

Table 2.2. Relationships between life events and transfers

	(A) Parent-to-child transfer probability (%)			(B) Child-to-parent transfer probability (%)			(C) Future (parent-to-child) transfer probability (%)		
	Non-exp	Exp	Diff	Non-exp	Exp	Diff	Non-exp	Exp	Diff
Panel 1. Child' life events									
U.S.-born (Native)	20.6	25.6	5.0*	1.2	1.0	-0.2*	6.2	6.2	0.0
Mixed status	20.5	26.4	5.9*	1.7	1.1	-0.6*	6.1	6.3	0.2*
Immigrant	14.3	20.1	5.8*	4.9	4.0	-0.9*	4.4	4.5	0.1
Panel 2. Parent's life events									
U.S.-born (Native)	23.7	20.5	-3.2*	0.9	1.4	0.5*	6.6	5.8	-0.8*
Mixed status	23.1	19.8	-3.3*	1.1	1.9	0.8*	6.7	5.6	-1.1*
Immigrant	17.4	13.6	-3.8*	3.6	5.0	1.4*	4.9	3.9	-1.0*

Note: The sample consists of parent–child dyads where the child is over 18 years old and not living with the parent in HRS. "Non-exp" refers to people who do not experience any life events of child (or parent); "Exp" refers to people who experience at least one life event of child (or parent). The "Diff" column lists the mean probability differences between Non-exp and Exp groups (= Exp - Non-exp). Column (A) indicates the likelihood of parent-to-child transfers; Column (B) indicates the likelihood of child-to-parent transfers; Column (C) indicates the likelihood of future parent-to-child transfers. The numbers in each column represent the mean value for transfer probability. Data is sourced from HRS data from 1996 to 2018 years. Asterisk (*) indicates that the differences in mean values between those who do and do not experience life events are statistically significant at the 99% confidence level ($p < 0.01$).

Table 2.3. Effects of life events on transfers

	Parent-to-child transfer				Child-to-parent transfer				Future transfer	
	Probability (%)		Net-amount ($)		Probability (%)		Net-amount ($)		Probability (%)	
	(1) Model 1	(2) Model 2	(3) Model 1	(4) Model 2	(5) Model 1	(6) Model 2	(7) Model 1	(8) Model 2	(9) Model 1	(10) Model 2
Panel 1. Immigrant-mixed-native category (reference: native)										
Mixed status	0.008**	0.008**	0.105***	0.102***	0.000	0.001	0.053	0.057	0.017***	0.017***
	(0.004)	(0.004)	(0.030)	(0.030)	(0.001)	(0.001)	(0.103)	(0.103)	(0.004)	(0.004)
Immigrant	0.027***	0.028***	0.299***	0.298***	0.021***	0.021***	0.189**	0.185**	0.058***	0.058***
	(0.005)	(0.005)	(0.037)	(0.037)	(0.001)	(0.001)	(0.080)	(0.080)	(0.004)	(0.004)
Panel 2. Parent's life events										
Hospitalization	0.000	0.000	0.008	0.008		0.001		-0.035	-0.008***	-0.008***
	(0.003)	(0.003)	(0.017)	(0.017)		(0.001)		(0.054)	(0.002)	(0.002)
Disability	0.004	0.004	0.026	0.026		0.006***		-0.072	-0.031***	-0.031***
	(0.003)	(0.003)	(0.022)	(0.022)		(0.001)		(0.058)	(0.003)	(0.003)
Poor health	0.001	0.001	0.023	0.023		0.003***		0.025	-0.069***	-0.070***
	(0.004)	(0.004)	(0.034)	(0.034)		(0.001)		(0.080)	(0.004)	(0.004)
Widowhood	0.021	0.025	0.095	0.088		0.008		-0.317	0.014	0.014
	(0.024)	(0.024)	(0.160)	(0.160)		(0.007)		(0.482)	(0.022)	(0.022)
Wealth loss	0.004	0.003	0.116	0.115		0.000		-0.020	-0.022***	-0.022***
	(0.003)	(0.003)	(0.119)	(0.191)		(0.001)		(0.062)	(0.002)	(0.002)
Job loss	-0.005**	-0.005**	-0.002	-0.004		0.004***		0.039	-0.005**	-0.005**
	(0.002)	(0.002)	(0.022)	(0.022)		(0.001)		(0.067)	(0.003)	(0.003)
Panel 3. Child's life events										
Divorce		0.041***		0.038	0.001	0.001	-0.087	-0.084		-0.004
		(0.006)		(0.040)	(0.002)	(0.002)	(0.144)	(0.145)		(0.006)
Job loss		0.045***		-0.011	-0.007***	-0.007***	0.130	0.133		0.002
		(0.005)		(0.038)	(0.002)	(0.002)	(0.144)	(0.144)		(0.005)
Graduation		0.046***		0.181***	-0.001	-0.001	-0.306	-0.304		0.033***
		(0.008)		(0.043)	(0.002)	(0.002)	(0.225)	(0.226)		(0.007)
Marriage		0.062***		0.226***	0.001	0.001	0.090	0.088		0.003
		(0.004)		(0.030)	(0.001)	(0.001)	(0.112)	(0.112)		(0.004)
Childbirth		-0.003		-0.038	-0.001	-0.001	-0.023	-0.020		0.006**
		(0.003)		(0.023)	(0.001)	(0.001)	(0.079)	(0.079)		(0.003)
Observations	150,474	150,474	27,658	27,658	150,474	150,474	2,480	2,480	146,261	146,261
R-squared	0.132	0.134	0.132	0.135	0.014	0.016	0.187	0.188	0.331	0.331

Note: The sample consists of parent–child dyads where the child is over 18 years old and not living with the parent in HRS. Each column is based on a separate regression. Model 1 includes life events of transfer donors, based on OLS regression without family- and child-fixed effects. Model 2 additionally includes life events of transfer recipients. Columns (1) and (2) indicate estimates of the likelihood of parent-to-child transfer; Columns (5) and (6) represent those of child-to-parent transfer. Columns (3) and (4) indicate estimates of parent-to-child transfer (logged) amount conditional on positive values; Columns (7) and (8) represent those of child-to-parent transfer (logged) amount conditional on positive values. Columns (9) and (10) indicate estimates on the likelihood of future transfer from parent to child. The numbers in each column represent the coefficients on each covariate. Other characteristics of donors and recipients are not listed in the table. Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. Robust standard errors clustered at the parent level are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 2.4. Immigrant–mixed–native differences in the effects of life events on transfers

	Parent-to-child transfer						Child-to-parent transfer						Future transfer		
	Probability (%)			Net-amount ($)			Probability (%)			Net-amount ($)			Probability (%)		
	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 1	(5) Model 2	(6) Model 3	(7) Model 1	(8) Model 2	(9) Model 3	(10) Model 1	(11) Model 2	(12) Model 3	(13) Model 1	(14) Model 2	(15) Model 3
Panel 1. Immigrant-mixed-native category (reference: native)															
Mixed-status (Mixed)	-0.001			0.093**			0.001			-0.009			0.012**		
	(0.006)			(0.040)			(0.001)			(0.112)			(0.005)		
Immigrant (Immi)	0.025***			0.317***			0.019***			0.095			0.045***		
	(0.006)			(0.048)			(0.002)			(0.088)			(0.005)		
Panel 2. Parent's life events and interaction terms															
Mixed*Hospitalization	-0.000	-0.000	0.001	0.209	0.085	0.086			0.001			-0.022	0.013	0.011	0.014
	(0.005)	(0.005)	(0.004)	(0.269)	(0.116)	(0.101)			(0.003)			(0.367)	(0.009)	(0.014)	(0.018)
Mixed*Disability	-0.003	0.010	0.010	-0.262***	-0.056	0.038			0.015**			0.132**	-0.001	0.011	0.016
	(0.011)	(0.015)	(0.012)	(0.090)	(0.145)	(0.123)			(0.006)			(0.071)	(0.010)	(0.020)	(0.011)
Mixed*Poor health	0.027*	0.009	0.007	0.021	0.028	-0.116			0.004			-0.264	-0.049***	0.007	0.005
	(0.015)	(0.023)	(0.016)	(0.121)	(0.271)	(0.193)			(0.007)			(0.368)	(0.014)	(0.025)	(0.014)
Mixed*Widowhood	0.015	0.081	0.112	-0.762	-0.730	-0.574			-0.012			0.156	-0.139	-0.246	-0.256
	(0.111)	(0.120)	(0.112)	(0.961)	(0.704)	(0.880)			(0.017)			(0.267)	(0.110)	(0.209)	(0.207)
Mixed*Wealth loss	0.028**	0.025	0.018	0.090	-0.053	-0.016			-0.004			0.175	0.010	-0.014	-0.013
	(0.012)	(0.020)	(0.015)	(0.077)	(0.118)	(0.112)			(0.003)			(0.271)	(0.009)	(0.017)	(0.010)
Mixed*Job loss	-0.026**	-0.020**	-0.020**	-0.293***	-0.252**	-0.249**			-0.002			-0.197	-0.019*	-0.022**	-0.022**
	(0.011)	(0.009)	(0.010)	(0.084)	(0.109)	(0.109)			(0.003)			(0.389)	(0.011)	(0.010)	(0.010)
Immi*Hospitalization	0.019*	-0.013	-0.008	-0.030	-0.017	-0.012			0.004			-0.218	-0.025***	-0.018	-0.017
	(0.010)	(0.011)	(0.009)	(0.085)	(0.115)	(0.115)			(0.006)			(0.256)	(0.009)	(0.014)	(0.014)
Immi*Disability	-0.001	-0.007	-0.008	-0.347***	-0.038	-0.066			-0.010			-0.111	-0.019***	-0.009	-0.007
	(0.011)	(0.012)	(0.010)	(0.107)	(0.151)	(0.153)			(0.007)			(0.283)	(0.010)	(0.015)	(0.009)
Immi*Poor health	0.029*	0.008	0.005	-0.070	-0.152	-0.099			-0.004			-0.183	-0.065***	-0.003	-0.002
	(0.015)	(0.017)	(0.014)	(0.152)	(0.337)	(0.312)			(0.010)			(0.447)	(0.013)	(0.024)	(0.013)
Immi*Widowhood	0.091	-0.322	-0.318	1.047	0.785	0.789			-0.013			0.119	-0.105	-0.152	-0.142
	(0.114)	(0.295)	(0.201)	(0.939)	(0.730)	(0.762)			(0.015)			(0.159)	(0.111)	(0.121)	(0.111)
Immi*Wealth loss	0.010*	-0.000	-0.002	0.037	0.133	0.180			-0.001			-0.307	-0.015***	-0.011	-0.010
	(0.006)	(0.013)	(0.010)	(0.094)	(0.162)	(0.139)			(0.007)			(0.313)	(0.006)	(0.021)	(0.012)
Immi*Job loss	-0.024*	-0.022**	-0.022**	-0.319*	-0.269**	-0.264**			0.014*			0.143	-0.022*	-0.032*	-0.033***
	(0.013)	(0.011)	(0.012)	(0.178)	(0.110)	(0.110)			(0.008)			(0.279)	(0.012)	(0.018)	(0.010)
Hospitalization	-0.007*	0.003	0.005	-0.004	-0.025	-0.021			0.000			-0.015	-0.007***	-0.002	-0.002
	(0.004)	(0.002)	(0.003)	(0.018)	(0.026)	(0.026)			(0.001)			(0.134)	(0.002)	(0.004)	(0.002)
Disability	0.004	0.005	0.003	0.057**	0.067*	0.056			0.003**			0.242*	-0.033***	-0.000	-0.000
	(0.003)	(0.004)	(0.003)	(0.023)	(0.067)	(0.035)			(0.001)			(0.135)	(0.003)	(0.005)	(0.003)
Poor health	-0.009**	-0.001	-0.003	0.023	0.019	0.032			0.001			-0.045	-0.077***	-0.028***	-0.029***
	(0.005)	(0.006)	(0.005)	(0.036)	(0.054)	(0.056)			(0.002)			(0.213)	(0.004)	(0.008)	(0.004)
Widowhood	-0.003	-0.001	-0.015	0.085	-0.308**	-0.474**			0.009			-0.449	0.019	0.077	0.038
	(0.044)	(0.046)	(0.039)	(0.165)	(0.136)	(0.236)			(0.011)			(0.863)	(0.023)	(0.065)	(0.033)
Wealth loss	0.007*	-0.001	-0.001	0.120***	0.061	0.040			0.000			-0.125	-0.025***	-0.019***	-0.018***
	(0.004)	(0.004)	(0.003)	(0.021)	(0.051)	(0.031)			(0.001)			(0.127)	(0.002)	(0.004)	(0.002)
Job loss	-0.017**	-0.014*	-0.013*	-0.000	-0.020	-0.025			0.003**			-0.156	-0.004*	-0.004*	-0.004*
	(0.009)	(0.008)	(0.007)	(0.024)	(0.017)	(0.015)			(0.001)			(0.167)	(0.002)	(0.002)	(0.002)
Panel 3. Child's life events and interaction terms															
Mixed*Divorce			-0.020			0.064	-0.005**	-0.002	-0.002	0.769	0.731*	0.847			0.005
			(0.032)			(0.247)	(0.002)	(0.008)	(0.008)	(0.489)	(0.391)	(0.515)			(0.021)
Mixed*Job loss			0.035*			0.058	-0.001	-0.001	-0.002	-0.985***	-0.893**	-0.883**			-0.000
			(0.021)			(0.126)	(0.006)	(0.004)	(0.004)	(0.285)	(0.439)	(0.434)			(0.017)
Mixed*Graduation			-0.042			-0.424	-0.009	-0.006	-0.006	0.001	0.004	0.004			0.030
			(0.049)			(0.286)	(0.009)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)			(0.024)

Mixed*Marriage			-0.027*			0.002	0.002	0.004	0.001	-0.141	0.516	0.614			-0.022
			(0.015)			(0.161)	(0.005)	(0.004)	(0.003)	(0.420)	(0.368)	(0.510)			(0.014)
Mixed*Childbirth			0.023			-0.246	-0.017***	-0.014***	-0.014***	-0.648*	-0.032	-0.313			0.005
			(0.023)			(0.244)	(0.005)	(0.004)	(0.002)	(0.353)	(0.362)	(0.486)			(0.010)
Immi*Divorce			0.004			0.281	0.012	0.017	0.017	0.709	0.781	0.946			-0.002
			(0.032)			(0.300)	(0.008)	(0.017)	(0.018)	(0.547)	(0.565)	(0.838)			(0.024)
Immi*Job loss			0.038*			0.031	-0.036***	-0.030***	-0.029***	-0.220	-0.248	-0.164			-0.004
			(0.020)			(0.224)	(0.005)	(0.012)	(0.012)	(0.302)	(0.352)	(0.387)			(0.015)
Immi*Graduation			-0.051			0.352	-0.010	-0.020	-0.015	-0.095	-0.078	-0.137			-0.070
			(0.047)			(0.428)	(0.009)	(0.018)	(0.018)	(0.532)	(0.527)	(0.544)			(0.070)
Immi*Marriage			0.018			0.056	-0.006	-0.001	-0.000	0.463*	0.195	0.153			0.002
			(0.021)			(0.188)	(0.005)	(0.009)	(0.009)	(0.239)	(0.385)	(0.424)			(0.015)
Immi*Childbirth			-0.005			0.102	0.006	-0.003	-0.002	0.194	-0.078	-0.127			0.016
			(0.013)			(0.174)	(0.004)	(0.006)	(0.007)	(0.178)	(0.269)	(0.348)			(0.011)
Divorce			0.043***			0.179***	-0.000	0.003	0.003	-0.296*	-0.522	-0.538			0.004
			(0.009)			(0.064)	(0.002)	(0.002)	(0.002)	(0.169)	(0.607)	(0.400)			(0.006)
Job loss			0.020***			0.055**	-0.003*	-0.003*	-0.003*	0.127	0.102	-0.102*			0.004
			(0.008)			(0.027)	(0.002)	(0.002)	(0.002)	(0.163)	(0.210)	(0.060)			(0.005)
Graduation			0.043***			0.244***	0.001	0.002	0.002	-0.251	0.265	0.117			-0.004
			(0.014)			(0.076)	(0.003)	(0.003)	(0.003)	(0.252)	(0.346)	(0.412)			(0.007)
Marriage			0.034***			0.174***	-0.001	-0.000	-0.001	0.354**	-0.074	-0.088			0.003
			(0.007)			(0.056)	(0.001)	(0.002)	(0.002)	(0.142)	(0.258)	(0.299)			(0.004)
Childbirth			-0.040			-0.065	0.001	-0.000	-0.006	-0.055	0.033	0.090			-0.005
			(0.050)			(0.040)	(0.001)	(0.001)	(0.004)	(0.091)	(0.172)	(0.197)			(0.003)
Observations	150,474	149,887	142,351	27,658	25,920	21,185	150,474	142,386	142,351	2,480	1,135	1,133	146,261	145,676	138,157
R-squared	0.132	0.380	0.483	0.134	0.518	0.554	0.014	0.354	0.359	0.193	0.636	0.657	0.331	0.742	0.737

Note: The sample consists of parent–child dyads where the child is over 18 years old and not living with the parent in HRS. Each column is based on a separate regression. Model 1 includes life events of transfer donors based on the OLS model without fixed effects. Model 2 additionally includes a donor-fixed effect. Model 3 adds life events of transfer recipients and a recipient-fixed effect. Other characteristics of donors and recipients are not listed in the table. The numbers in each column represent the coefficients on each covariate. Data is sourced from HRS data from 1996 to 2018 years. All regressions are weighted. Robust standard errors clustered at the parent level are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 2.5. Robustness checks (continued)

	Parent-child transfer								Child-parent transfer	
	Probability (%)				Net-amount ($)				Probability (%)	
	(1) Main Model	(2) Model 2	(3) Model 3	(4) Model 4	(5) Main Model	(6) Model 2	(7) Model 3	(8) Model 4	(9) Main Model	(10) Model 2
Panel 1. Parent's events and interaction terms										
Mixed*Hospitalization	0.001	0.003	0.005	-0.132	0.086	0.085	0.092	-0.118	0.001	0.001
	(0.004)	(0.011)	(0.016)	(0.169)	(0.101)	(0.101)	(0.232)	(0.108)	(0.003)	(0.003)
Mixed*Disability	0.010	0.008	0.004	0.109	0.038	0.030	0.034	0.262	0.015**	0.016**
	(0.012)	(0.012)	(0.017)	(0.123)	(0.123)	(0.126)	(0.136)	(0.334)	(0.006)	(0.007)
Mixed*Poor health	0.007	0.005	0.003	0.192	-0.116	-0.101	-0.113	-0.278	0.004	0.006
	(0.016)	(0.044)	(0.019)	(0.217)	(0.193)	(0.500)	(0.283)	(0.202)	(0.007)	(0.016)
Mixed*Widowhood	0.112	0.110	0.133	0.042	-0.574	-0.564	-0.577	-1.061**	-0.012	-0.016
	(0.112)	(0.121)	(0.183)	(0.141)	(0.880)	(0.914)	(0.698)	(0.511)	(0.017)	(0.018)
Mixed*Wealth loss	0.018	0.017	0.016	0.102	-0.016	-0.018	-0.118	-0.091	-0.004	-0.004
	(0.015)	(0.015)	(0.019)	(0.302)	(0.112)	(0.111)	(0.151)	(0.115)	(0.003)	(0.003)
Mixed*Job loss	-0.020**	-0.025**	-0.023*	0.023	-0.249**	-0.250**	-0.219*	0.408	-0.002	-0.002
	(0.010)	(0.012)	(0.013)	(0.099)	(0.109)	(0.109)	(0.129)	(0.415)	(0.003)	(0.003)
Immi*Hospitalization	-0.008	-0.008	-0.013	0.020*	-0.012	-0.011	-0.017	0.014	0.004	0.005
	(0.009)	(0.009)	(0.013)	(0.011)	(0.115)	(0.115)	(0.153)	(0.116)	(0.006)	(0.006)
Immi*Disability	-0.008	-0.009	-0.010	0.001	-0.066	-0.054	-0.152	-0.086	-0.010	-0.008
	(0.010)	(0.010)	(0.012)	(0.021)	(0.153)	(0.155)	(0.182)	(0.164)	(0.007)	(0.007)
Immi*Poor health	0.005	0.004	0.008	-0.003	-0.099	-0.103	-0.105	-0.136	-0.004	-0.005
	(0.014)	(0.035)	(0.020)	(0.013)	(0.312)	(0.514)	(0.386)	(0.308)	(0.010)	(0.018)
Immi*Widowhood	-0.318	-0.303	-0.307	0.204	0.789	0.790	0.736	0.497	-0.013	-0.014
	(0.201)	(0.201)	(0.293)	(0.302)	(0.762)	(0.767)	(0.748)	(0.364)	(0.015)	(0.015)
Immi*Wealth loss	-0.002	-0.002	-0.005	0.000	0.180	0.178	0.040	0.102	-0.001	-0.001
	(0.010)	(0.010)	(0.015)	(0.011)	(0.139)	(0.137)	(0.163)	(0.145)	(0.007)	(0.007)
Immi*Job loss	-0.022**	-0.024**	-0.023*	-0.019	-0.264**	-0.230**	-0.229*	0.240	0.014*	0.014*
	(0.012)	(0.012)	(0.013)	(0.022)	(0.110)	(0.116)	(0.132)	(0.266)	(0.008)	(0.008)
Hospitalization	0.005	0.005	0.008	-0.003	-0.021	-0.017	-0.016	-0.005	0.000	0.000
	(0.003)	(0.004)	(0.006)	(0.023)	(0.026)	(0.026)	(0.031)	(0.028)	(0.001)	(0.001)
Disability	0.003	0.003	0.002	-0.005	0.056	0.061*	0.064	0.056	0.003**	0.007***
	(0.003)	(0.003)	(0.004)	(0.014)	(0.035)	(0.033)	(0.074)	(0.037)	(0.001)	(0.002)
Poor health	-0.003	-0.004	-0.005	-0.105	0.032	0.038	0.043	-0.025	0.001	0.002
	(0.005)	(0.013)	(0.006)	(0.015)	(0.056)	(0.046)	(0.058)	(0.059)	(0.002)	(0.002)
Widowhood	-0.015	-0.018	-0.014	-0.002	-0.474**	-0.495**	-0.447**	0.064	0.009	0.011
	(0.039)	(0.039)	(0.028)	(0.044)	(0.236)	(0.238)	(0.219)	(0.093)	(0.011)	(0.012)
Wealth loss	-0.001	-0.001	-0.003	-0.002	0.040	0.042	0.042	-0.094	0.000	0.000
	(0.003)	(0.003)	(0.005)	(0.004)	(0.031)	(0.031)	(0.043)	(0.093)	(0.001)	(0.001)
Job loss	-0.013*	-0.005*	-0.007**	-0.005	-0.025	-0.022	-0.020	0.217	0.003**	0.005*
	(0.007)	(0.003)	(0.003)	(0.005)	(0.015)	(0.035)	(0.046)	(0.236)	(0.001)	(0.003)
Panel 2. Child's events and interaction terms										
Mixed*Divorce	-0.020	-0.021	-0.021	-0.026	0.064	0.068	0.068	0.038	-0.002	-0.002
	(0.032)	(0.032)	(0.022)	(0.032)	(0.247)	(0.249)	(0.151)	(0.358)	(0.008)	(0.008)
Mixed*Job loss	0.035*	0.037*	0.042**	-0.036	0.058	0.050	0.060	0.138	0.002	-0.002
	(0.021)	(0.021)	(0.018)	(0.073)	(0.126)	(0.128)	(0.153)	(0.241)	(0.004)	(0.004)
Mixed*Graduation	-0.042	-0.039	-0.043	0.063	-0.424	-0.410	-0.474	0.971	-0.006	-0.006
	(0.049)	(0.049)	(0.040)	(0.090)	(0.286)	(0.286)	(0.415)	(0.994)	(0.004)	(0.004)
Mixed*Marriage	-0.027*	-0.028*	-0.035**	0.013	0.002	0.012	0.012	0.405	0.001	0.001
	(0.015)	(0.015)	(0.018)	(0.103)	(0.161)	(0.160)	(0.100)	(0.467)	(0.003)	(0.003)
Mixed*Childbirth	0.023	0.024	0.029	-0.005	-0.246	-0.243	-0.272	0.157	-0.014***	-0.014***
	(0.023)	(0.023)	(0.025)	(0.013)	(0.244)	(0.264)	(0.396)	(0.141)	(0.002)	(0.002)
Immi*Divorce	0.004	0.004	0.005	0.001	0.281	0.296	0.263	-0.468	0.017	0.017
	(0.032)	(0.032)	(0.021)	(0.092)	(0.300)	(0.303)	(0.282)	(0.315)	(0.018)	(0.018)
Immi*Job loss	0.038*	0.034*	0.037*	-0.028	0.031	0.035	0.039	0.306	-0.029***	0.024***
	(0.020)	(0.018)	(0.017)	(0.060)	(0.224)	(0.223)	(0.275)	(0.427)	(0.012)	(0.003)
Immi*Graduation	-0.051	-0.049	0.048	0.005	0.352	0.326	0.337	0.177***	-0.015	-0.015
	(0.047)	(0.047)	(0.035)	(0.092)	(0.428)	(0.429)	(0.511)	(0.063)	(0.018)	(0.018)
Immi*Marriage	0.018	0.010	0.011	-0.012	0.056	0.059	0.069	0.036	-0.000	-0.000
	(0.021)	(0.020)	(0.020)	(0.032)	(0.188)	(0.190)	(0.112)	(0.205)	(0.009)	(0.012)
Immi*Childbirth	-0.005	-0.004	-0.009	0.009*	0.102	0.115	0.118	0.070	-0.002	-0.002
	(0.013)	(0.013)	(0.020)	(0.005)	(0.174)	(0.174)	(0.276)	(0.183)	(0.007)	(0.007)
Divorce	0.043***	0.044***	0.043***	-0.000	0.179***	0.179***	0.158***	-0.377	0.003	0.003
	(0.009)	(0.009)	(0.006)	(0.000)	(0.064)	(0.064)	(0.046)	(0.463)	(0.002)	(0.002)
Job loss	0.020***	0.021***	0.022***	-0.018	0.055**	0.058**	0.073*	-0.222	-0.003*	-0.003*
	(0.008)	(0.008)	(0.006)	(0.020)	(0.027)	(0.029)	(0.041)	(0.211)	(0.002)	(0.002)
Graduation	0.043***	0.041***	0.042***	0.012	0.244***	0.240***	0.227***	-0.451	0.002	0.002
	(0.014)	(0.014)	(0.014)	(0.029)	(0.076)	(0.076)	(0.080)	(0.477)	(0.003)	(0.003)
Marriage	0.034***	0.032***	0.031***	-0.001	0.174***	0.171***	0.218**	-0.190	-0.001	-0.001
	(0.007)	(0.007)	(0.008)	(0.008)	(0.056)	(0.056)	(0.096)	(0.256)	(0.002)	(0.002)
Childbirth	-0.040	-0.004	-0.004	0.002	-0.065	-0.066*	-0.081	-0.259	-0.006	-0.006
	(0.050)	(0.005)	(0.008)	(0.005)	(0.040)	(0.039)	(0.066)	(0.260)	(0.004)	(0.004)
Observations	142,351	142,324	86,695	135,153	21,185	21,181	12,220	19,999	142,351	142,324
R-squared	0.483	0.484	0.469	0.126	0.554	0.555	0.541	0.142	0.359	0.359

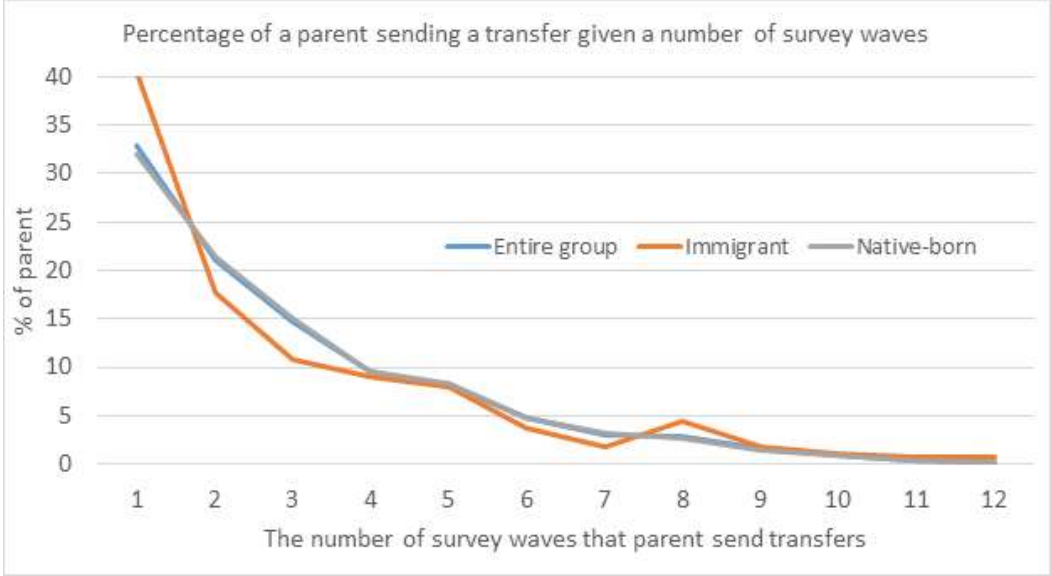
Note: The sample consists of non-coresident parent–child dyads where the child is over 18 years. Column 1 indicates main estimates. Model 2 includes a predicted probability of poor health status instead of a self-reported health measure in the HRS. Model 3 is based on a sample limited to those who do not experience older parental death. Model 4 represents estimates on leaded outcomes (*t-1*). *** p<0.01 ** p<0.05 * p<0.1

Table 2.5. Robustness checks

	Child-parent transfer						Future transfer			
	Probability (%)		Net-amount ($)				Probability (%)			
	(11) Model 3	(12) Model 4	(13) Main Model	(14) Model 2	(15) Model 3	(16) Model 4	(17) Main Model	(18) Model 2	(19) Model 3	(20) Model 4
Panel 1. Parent's events and interaction terms										
Mixed*Hospitalization	0.001	0.011	-0.022	-0.044	-0.406	-0.015	0.014	0.014	0.012	-0.309
	(0.003)	(0.093)	(0.367)	(0.358)	(0.344)	(0.368)	(0.018)	(0.018)	(0.009)	(0.302)
Mixed*Disability	0.014***	0.058	0.132**	0.173	0.143	0.006	0.016	0.010	0.012	0.108
	(0.004)	(0.059)	(0.071)	(0.176)	(0.154)	(0.093)	(0.011)	(0.011)	(0.011)	(0.211)
Mixed*Poor health	0.004	0.005	-0.264	-0.241	-0.214	-0.259	0.005	0.005	0.008	-0.094
	(0.010)	(0.007)	(0.368)	(0.285)	(0.443)	(0.368)	(0.014)	(0.010)	(0.016)	(0.095)
Mixed*Widowhood	-0.010	-0.015**	0.156	0.152	0.129	0.559	-0.256	-0.296	-0.199	-0.050
	(0.011)	(0.006)	(0.267)	(0.293)	(0.305)	(0.551)	(0.207)	(0.299)	(0.272)	(0.078)
Mixed*Wealth loss	-0.005	-0.003	0.175	0.176	0.195	-0.149	-0.013	-0.014	-0.017	-0.105
	(0.005)	(0.014)	(0.271)	(0.249)	(0.307)	(0.472)	(0.010)	(0.010)	(0.015)	(0.110)
Mixed*Job loss	-0.003	-0.002	-0.197	-0.184	-0.197	-0.181	-0.022**	-0.021**	-0.024*	-0.223
	(0.004)	(0.013)	(0.389)	(0.401)	(0.347)	(0.486)	(0.010)	(0.010)	(0.013)	(0.310)
Immi*Hospitalization	0.006	0.007	-0.218	-0.246	-0.374	0.993	-0.017	-0.017	-0.019	-0.319
	(0.007)	(0.016)	(0.256)	(0.255)	(0.418)	(0.963)	(0.014)	(0.018)	(0.020)	(0.428)
Immi*Disability	-0.007	-0.011	-0.111	-0.204	-0.230	0.401	-0.007	-0.007	-0.014	0.312
	(0.010)	(0.017)	(0.283)	(0.401)	(0.347)	(0.602)	(0.009)	(0.009)	(0.013)	(0.309)
Immi*Poor health	-0.006	-0.007	-0.183	-0.201	-0.221	0.996	-0.002	-0.003	-0.008	0.111
	(0.011)	(0.018)	(0.447)	(1.045)	(0.462)	(0.981)	(0.013)	(0.014)	(0.014)	(0.114)
Immi*Widowhood	-0.015	-0.010	0.119	0.112	0.104	-0.159	-0.142	-0.127	-0.135	0.035
	(0.018)	(0.033)	(0.159)	(0.193)	(0.105)	(0.251)	(0.111)	(0.136)	(0.177)	(0.177)
Immi*Wealth loss	0.000	-0.027***	-0.307	-0.304	-0.335	0.892	-0.010	-0.009	-0.004	-0.110
	(0.004)	(0.009)	(0.313)	(0.317)	(0.374)	(0.919)	(0.012)	(0.012)	(0.014)	(0.112)
Immi*Job loss	0.014*	-0.060	0.143	0.132	0.125	0.459	-0.033***	-0.034***	-0.025***	0.335
	(0.008)	(0.093)	(0.279)	(0.283)	(0.765)	(0.500)	(0.010)	(0.011)	(0.009)	(0.411)
Hospitalization	0.002*	-0.010	-0.015	-0.014	-0.023	-0.217	-0.002	-0.003	-0.009	0.302
	(0.001)	(0.014)	(0.134)	(0.134)	(0.134)	(0.233)	(0.002)	(0.002)	(0.010)	(0.402)
Disability	0.005***	-0.094	0.242*	0.249**	0.281**	-0.733	-0.000	0.001	-0.009***	-0.243
	(0.002)	(0.097)	(0.135)	(0.131)	(0.143)	(0.737)	(0.003)	(0.003)	(0.003)	(0.244)
Poor health	0.003	0.031	-0.045	-0.076	-0.059	0.207	-0.029***	-0.035***	-0.034***	-0.129
	(0.002)	(0.092)	(0.213)	(0.326)	(0.279)	(0.212)	(0.004)	(0.003)	(0.005)	(0.134)
Widowhood	0.011	0.009	-0.449	-1.430*	-1.112	0.812	0.038	0.030	0.035	-0.137
	(0.015)	(0.012)	(0.863)	(0.816)	(1.127)	(0.869)	(0.033)	(0.032)	(0.026)	(0.234)
Wealth loss	0.000	0.020	-0.125	-0.241**	-0.244***	1.260	-0.018***	-0.018***	-0.024***	0.417
	(0.009)	(0.021)	(0.127)	(0.128)	(0.087)	(1.128)	(0.002)	(0.002)	(0.004)	(0.562)
Job loss	0.007**	0.032	-0.156	-0.175	-0.198	0.856	-0.004*	-0.003***	-0.006*	-0.022
	(0.003)	(0.034)	(0.167)	(0.170)	(0.260)	(0.976)	(0.002)	(0.001)	(0.004)	(0.031)
Panel 2. Child's events and interaction terms										
Mixed*Divorce	-0.003	0.030***	0.847	0.881	0.781	-0.800	0.005	0.003	0.003	0.154
	(0.004)	(0.009)	(0.515)	(0.887)	(0.879)	(0.819)	(0.021)	(0.021)	(0.003)	(0.161)
Mixed*Job loss	0.002	0.042	-0.883**	-0.949*	-0.961***	-1.022	-0.000	-0.001	-0.002	-0.202
	(0.005)	(0.055)	(0.434)	(0.519)	(0.238)	(1.009)	(0.017)	(0.017)	(0.013)	(0.315)
Mixed*Graduation	-0.005	-0.094	0.004	0.222	0.183	0.913	0.030	0.026	0.025	-0.302
	(0.006)	(0.102)	(0.003)	(0.310)	(0.210)	(0.989)	(0.024)	(0.024)	(0.032)	(0.342)
Mixed*Marriage	0.002	0.102	0.614	0.406	0.631	-0.931	-0.022	-0.022	-0.022	-0.009
	(0.004)	(0.184)	(0.510)	(0.652)	(0.538)	(0.938)	(0.014)	(0.014)	(0.015)	(0.013)
Mixed*Childbirth	-0.012***	0.104	-0.313	-0.371	-0.419	0.898	0.005	0.006	-0.014	-0.003
	(0.004)	(0.182)	(0.486)	(0.478)	(0.497)	(0.987)	(0.010)	(0.010)	(0.014)	(0.009)
Immi*Divorce	0.019	0.106	0.946	0.959	0.284	0.871	-0.002	-0.003	-0.008	-0.104
	(0.020)	(0.200)	(0.838)	(0.831)	(0.568)	(0.872)	(0.024)	(0.024)	(0.015)	(0.125)
Immi*Job loss	0.022*	-0.082	-0.164	-0.167	-0.176	0.838	-0.004	-0.003	-0.003	0.095
	(0.011)	(0.091)	(0.387)	(0.373)	(0.478)	(0.995)	(0.015)	(0.015)	(0.012)	(0.095)
Immi*Graduation	-0.018	0.018	-0.137	-1.084*	-0.335	0.184	-0.070	-0.071	-0.050	-0.058**
	(0.019)	(0.020)	(0.544)	(0.625)	(0.944)	(0.663)	(0.070)	(0.076)	(0.068)	(0.028)
Immi*Marriage	-0.001	-0.013	0.153	0.143	0.106	-0.806	0.002	0.002	0.001	0.196
	(0.008)	(0.029)	(0.424)	(0.416)	(0.485)	(0.885)	(0.015)	(0.015)	(0.013)	(0.197)
Immi*Childbirth	-0.005	0.002	-0.127	-0.101	-0.166	0.085	0.016	0.016	0.015	-0.139
	(0.010)	(0.009)	(0.348)	(0.344)	(0.511)	(0.373)	(0.011)	(0.011)	(0.017)	(0.152)
Divorce	0.002	0.102**	-0.538	-0.538	-0.557	-0.983	0.004	0.004	0.008	-0.082
	(0.002)	(0.050)	(0.400)	(0.404)	(0.467)	(0.905)	(0.006)	(0.006)	(0.009)	(0.085)
Job loss	-0.003*	0.101	-0.102*	-0.107*	-0.106*	0.520	0.004	0.004	0.004	-0.005
	(0.002)	(0.109)	(0.060)	(0.061)	(0.059)	(0.962)	(0.005)	(0.005)	(0.005)	(0.006)
Graduation	0.003	0.084	0.117	0.117	0.129	0.940	-0.004	-0.004	-0.003	-0.109
	(0.003)	(0.093)	(0.412)	(0.393)	(0.666)	(0.981)	(0.007)	(0.007)	(0.009)	(0.107)
Marriage	-0.000	-0.100	-0.088	-0.111	-0.112	0.612	0.003	0.003	0.004	0.904
	(0.002)	(0.092)	(0.299)	(0.301)	(0.314)	(0.914)	(0.004)	(0.004)	(0.004)	(0.913)
Childbirth	-0.002	-0.109	0.090	0.094	-0.017	1.098	-0.005	-0.005	-0.007	0.063
	(0.002)	(0.120)	(0.197)	(0.195)	(0.332)	(1.093)	(0.003)	(0.003)	(0.005)	(0.093)
Observations	86,695	135,153	1,133	1,133	561	1,094	138,157	138,118	83,601	126,081
R-squared	0.359	0.109	0.657	0.658	0.651	0.157	0.737	0.737	0.734	0.124

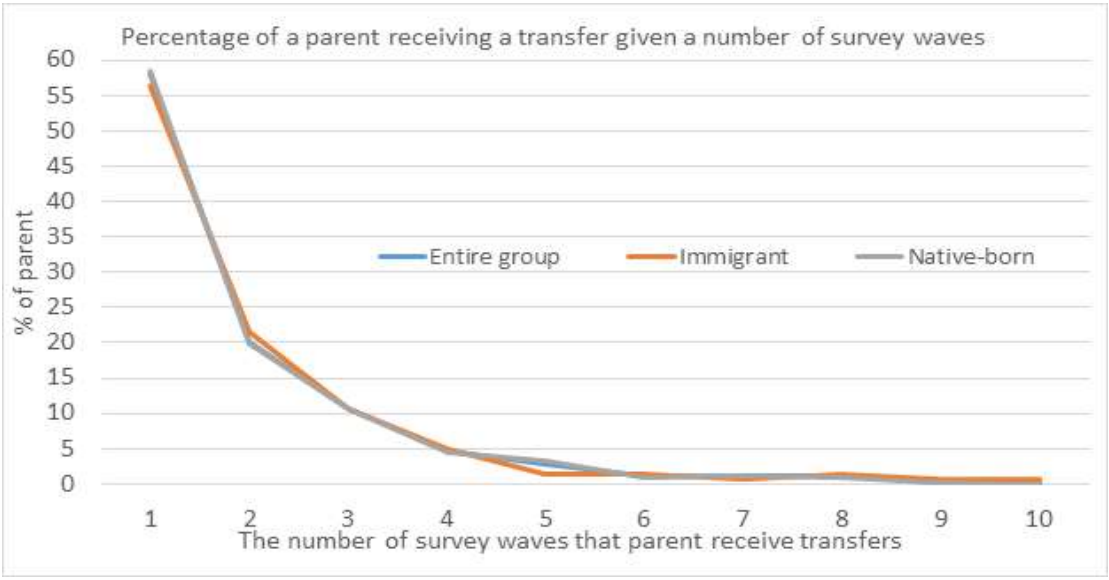
Note: The sample consists of non-coresident parent–child dyads where the child is over 18 years. Column 1 indicates main estimates. Model 2 includes a predicted probability of poor health status instead of a self-reported health measure in the HRS. Model 3 is based on a sample limited to those who do not experience older parental death. Model 4 represents estimates on leaded outcomes (*t-1*). *** p<0.01 ** p<0.05 * p<0.1

Appendix Figure A2.1. Percentage of a parent sending a transfer given the number of survey waves



Note: The sample is restricted to respondents (older parents) who were born between 1931 and 1941, and who continuously participated in twelve waves of the HRS survey. The sample includes parents who have sent transfers to their children at least once throughout the survey waves (N=2,876). The X-axis represents the number of survey waves in which each parent sends transfers, meaning the frequency of transfers ranges from 1 to 12. The Y-axis indicates the percentage of parents by the number of survey waves in which they sent transfers. The blue line indicates descriptive data for the entire sample, the orange line represents the immigrant group, and the grey line corresponds to the U.S. native-born group. Data is sourced from HRS data spanning the years 1996 to 2018.

Appendix Figure A2.2. Percentage of a parent receiving a transfer given the number of survey waves



Note: The sample is restricted to respondents (older parents) who were born between 1931 and 1941, and who continuously participated in twelve waves of the HRS survey. The sample includes parents who have received transfers from their children at least once throughout the survey waves (N=655). The X-axis represents the number of survey waves in which each parent receives transfers, meaning the frequency of transfers ranges from 1 to 10. The Y-axis indicates the percentage of parents by the number of survey waves in which they received transfers. The blue line indicates descriptive data for the entire sample, the orange line represents the immigrant group, and the grey line corresponds to the U.S. native-born group. Data is sourced from HRS data spanning the years 1996 to 2018.

Paper 3: U.S. Social Security program and intergenerational transfers of immigrants and native-born citizens

1. Introduction

The U.S. Social Security program, a retirement insurance plan, is the largest component of the federal budget targeting most people over age 65 (e.g., 91.3% in 2020) (Social Security Administration [SSA], 2022). This program elevates more elderly people from poverty than any other program (Romig, 2022). Arguably, it also helps children of Social Security recipients through intergenerational transfers. In response to the program, the children of Social Security recipients may reduce support they provide to their parents. Social Security recipients may in turn increase support that they provide to their children. Thus, investigating the direction and magnitude of intergenerational transfers corresponding to Social Security can clarify how Social Security might affect the lives of older parents and their children. The main focus of this study is to investigate how the Social Security program impacts intergenerational transfers (from parents to children, and from children to parents) and whether the impact differs between immigrant and native families.

Notably, the Social Security program may influence intergenerational transfers in immigrant and native families differently on account of limited Social Security eligibility among immigrant families as well as on account of differences in the salience of intergenerational transfers between these two groups. Paper 1 underscored the higher reliance of older immigrants on intergenerational transfer than comparable U.S.-born (Albertini et al., 2007). Such discrepancies might also arise from older immigrants' Social Security eligibility—the program

requires 40 quarters of work, a criterion that fairly few immigrants meet (SSA, 2022). Two-thirds of never-beneficiaries are immigrants (SSA, 2021; Whitman et al., 2011).

This paper aims: 1) to investigate the effects of older parents' Social Security eligibility on parent-to-child and child-to-parent financial transfers; and 2) to determine whether estimates differ across foreign-born and U.S.-born older adults. The current study contributes to the existing literature in two ways. This is the first study to investigate immigrant–native differences in transfer decisions in relation to the U.S. Social Security program. Prior studies focused on differences in transfers by race and/or ethnicity, not immigration status (Smythe, 2019). Second, this study explores parent-to-child and child-to-parent transfers within the U.S. context. Prior works centered on one transfer direction and often considered means-tested programs in developing countries (Nikolov & Bonci, 2020), which may not generalize to the Social Security program in the U.S.

Disentangling the relationship between Social Security and familial economic security via intergenerational transfers has policy lessons. Reducing Social Security benefits might lower intergenerational transfers. Numerous reform proposals have been aimed at reducing benefits and coverage duration of Social Security (Congressional Research Service [CRS], 2022).[18] It can harm older parents and likely their children if parents become more dependent on their children (or lower transfers to children) in response to such policy changes. Thus, the program's effectiveness is more thoroughly assessed by including impacts on intergenerational transfers.

The empirical analysis is based on a quasi-experimental design called regression discontinuity design (RDD), which is commonly used in this line of research. RDD is a pretest-

[18] The Social Security fund is expected to be depleted by 2037 (Goss, 2010). To mitigate fiscal imbalance of this program, Social Security Administration (SSA) proposed increasing the earliest eligibility age (EEA) by two months per year from age 62 to 65 by 2040 (CRS, 2022).

posttest design that determines the causal effects of an intervention by assigning a threshold above and below the intervention. I use the earliest eligible age (age 62) for the U.S. Social Security program as the cutoff (or threshold) and estimate if intergenerational transfer behaviors of observations lying closely on either side of the threshold change in response to the intervention.

2. Literature Review

Theoretical considerations

The literature has scrutinized the responsiveness of intergenerational transfers to income changes, focusing on transfer motivation (Laferrère & Wolff, 2006). Among various theoretical models, altruism models posit that transfer donors care about transfer recipients' hardships and provide transfers to reduce those hardships (Barro, 1974; Becker, 1974).[19] Such models predict that older parents' receipt of Social Security benefits leads to an increase in parent-to-child transfers and a decline in child-to-parent transfer (i.e., crowding-out effect), as parents become wealthier than before. The models can offer a basis for the theoretical rationale behind the expected impact of Social Security on intergenerational transfers and corresponding differences across subgroups.

Empirical evidence

Several researchers have investigated how public pensions impact private transfers: from children to their parents (pension recipients) and from parents (also pension recipients) to their children. One strand of work on child-to-parent transfers has addressed to what extent pension

[19] Conversely, the exchange model posits that individuals' transfer behaviors are based on economic exchanges (Cox et al., 1998). For example, if no exchange of goods or services takes place between parents and children, shifts in intergenerational transfers may not occur, irrespective of whether older parents receive Social Security benefits or not.

benefits decrease or increase intergenerational transfers (Cox et al., 1998; Cox & Jimenez, 1992; Gibson et al., 2011; Lai & Orsuwan, 2009; Maitra & Ray, 2003). Such studies have shown that public pensions generally displace private transfers, suggesting that intergenerational transfer decisions are inherently altruistic. Most research in this field has exclusively analyzed means-tested programs (public pension programs) in developing countries; examples include Mexico (Amuedo-Dorantes & Juarez, 2013; Galiani et al., 2016), Papua New Guinea (Gibson et al., 2011), Peru (Cox & Jimenez, 1992; Cox et al., 1998; Juarez, 2009), and South Africa (Jensen, 2003; Maitra & Ray, 2003).[20] Their findings may not generalize to the U.S. setting due to the unique features of the Social Security program, resource constraints, institutional settings, and policy environments (Kaushal, 2014).[21] Empirically, Nikolov and Bonci (2020) found that the effect sizes for developed-country cases were far more modest than those for developing countries. Theoretically, the Social Security program, which requires benefit recipients' contributions, may diverge from means-tested cash transfer programs. Social Security induces changes in intertemporal resource allocations via (early) access to benefits, whereas means-tested transfer programs involve income changes separate from intertemporal decisions (Kim & Koh, 2020).

Another stream of research has explored transfers from older adults to determine how pensions benefit other family members. Some studies pointed out that Social Security increased parent-to-child transfers, albeit modestly (Chuang, 2012; S. Lee et al., 2019; Mudrazija, 2014). Case and Deaton (1998) considered the impacts of social pensions on employment, educational expenses, and parent-to-child transfers as resource allocation behaviors. They mentioned that their

[20] U.S.-based studies have mostly examined the impact of public transfers aimed at "(adult) children" on parent-to-child transfers; for instance, Schoeni (2002) found a 20 percent crowding-out effect of Unemployment Insurance on parent-to-child transfers.
[21] Developed countries have a more extensive history of public transfers, which might have slowly undermined informal safety nets, such as family transfers (Nikolov & Bonci, 2020). In addition, formal private insurance markets in developing countries are largely underdeveloped whereas those in developed countries are well-established (Roth et al., 2007)

study might not fully capture how pension benefits are shared with other family members; the authors did not consider child-to-parent transfers. Limited consideration of transfers' two-sided nature may obscure the nuances of transfer schemes (Laitner, 1997); for example, pension benefits can be "passed on" to a child (parent-to-child transfer), and simultaneously can "crowd out" support from the child (child-to-parent transfer).

Two recent U.S.-based studies covering parent-to-child and child-to-parent transfers are relevant to this paper. Mukherjee (2022) reported that the likelihood and amount of parent-to-child financial transfers increased in response to more Social Security benefits; child-to-parent financial transfers presented non-significant estimates in contrast to prior research. Smythe (2019) discerned the impact of Social Security eligibility on transfer probability using the earliest eligible age (EEA) via a regression discontinuity design. Different from Mukherjee (2022), Smythe (2019) showed that the probability of child-to-parent and parent-to-child transfers reduced after crossing the age eligibility threshold, with these effects being pronounced for Black and low-income families based on separate subset samples. Discrepant findings may be due to potential biases, such as those stemming from distorted behaviors of prospective benefit recipients or parametric model specification (Barreca et al., 2016; Calonico et al., 2014, 2015, 2017, 2019). Furthermore, the Social Security Notch in the prior study pertained to a specific cohort born between 1917 and 1921. [22] Arguably, factors related to transfer decisions may have changed over time.

Moreover, no research to my knowledge appears to have explored immigrant–native differences in intergenerational transfers in response to the U.S. Social Security.[23] Heterogeneous

[22] The Social Security Notch refers to an accidental variation in Social Security benefits for individuals born between 1917 and 1921, caused by an error in the inflation adjustment formula used by the Social Security Administration in 1972 (Mukherjee, 2022).
[23] Prior studies have investigated heterogeneous effects by gender (Amuedo-Dorantes & Juarez, 2013; Jensen, 2003; Mukherjee, 2022), poverty status (Nikolov & Adelman, 2019; Oruc, 2011), race and ethnicity (Mukherjee, 2022; Smythe, 2019), education (Mejía-Guevara, 2015; Mukherjee, 2022), and rural-urban differences (Cox & Jimenez, 1995; Cox et al., 2004; Gibson et al., 2011).

effects between these groups are nonetheless possible for a number of reasons. First, due to short employment histories and lower average earnings, immigrants are less likely to receive Social Security (or receive lower Social Security benefits, if eligible) compared to native-born (Favreault & Nichols, 2012; Sevak & Schmidt, 2014). The probability of benefit receipt and its size affect beneficiaries' intergenerational transfer patterns (Nikolov & Bonci, 2020). Second, immigrants typically possess insufficient retirement resources (e.g., wealth and private pensions) compared with native-born and may instead rely on familial transfers (Amuedo-Dorantes & Pozo, 2002; Heim et al., 2012). Paper 2 demonstrated immigrants' greater responsiveness (vs. native-born counterparts) to job loss, including retirement, compared with other life events. Third, cultural factors could influence immigrants' transfer behavior as well (Albertini et al., 2019). Strong altruistic cohesion in immigrant families can enhance their intergenerational support, as posited by the solidarity hypothesis (Dumon, 1989; Nauck, 2001). Conversely, immigrants may exhibit less responsive intergenerational support due to tensions from generational and cultural divergences according to the conflict hypothesis (Merz et al., 2009).

3. Institutional background: U.S. Social Security program and the earliest eligible age

The Social Security program in the U.S. offers monthly financial benefits to eligible retired or disabled workers as well as their dependents and survivors.[24] Individuals must meet two criteria for coverage in relation to employment and age. First, a person must have worked for at least 40 covered quarters (10 years) in the formal sector and thus contributed to their social security (Cohen & Iams, 2007; SSA, 2022). Immigrants with inadequate employment backgrounds primarily

[24] This study does not consider disabled workers, and dependents and survivors of retired workers.

constitute a substantial proportion of the older people in the U.S. who are ineligible for Social Security (SSA, 2021; Whitman et al., 2011). Second, individuals have to be at least 62 years of age to be eligible for Social Security (non-disability cases). The Full retirement age (FRA) is between 65 and 67 depending on one's birth cohort; the earliest eligible age (EEA) is 62, but claiming at this age results in reduced benefits.

This study exploits eligibility to receive Social Security benefits at the earliest eligible age (EEA) of 62, which lends several advantages to the research design. First, it can minimize potential biases from the effects of other federal and state programs for which the eligible age is 65 (e.g., Medicare). Second, the largest proportion of recipients (e.g., 29.3%) opts to receive Social Security benefits at this age (CRS, 2022). Third, people who claim Social Security at the EEA represent a relatively vulnerable population requiring support, such as intergenerational transfers (Li et al., 2008).[25]

4. Method

Data and sample

This study utilizes data from twelve survey waves based on HRS restricted-use data merged with public-use HRS files between 1996 and 2018. Public-use HRS data provide details on the socioeconomic and demographic characteristics of the respondents, their year of birth, Social Security benefit receipt and amount, and intergenerational financial transfers. HRS restricted-use data offer precise months of respondents' interviews and births, which is essential for the research

[25] Li et al. (2008) suggested that people who receive Social Security at the Early Eligibility Age (EEA) typically have poorer health, lower educational attainment, reduced earnings, and jobs that are more physically strenuous compared to those who begin receiving benefits after the EEA.

design I adopted in this paper, namely, regression discontinuity design (RDD). The details of the RDD are presented in the next section.

The sample unit consists of a parent–child dyad in a non-coresident family to account for a parent's and a child's characteristics that influence transfer decisions, as discussed in Papers 1 and 2. In this paper, the analytic sample is constructed in accordance with the Social Security eligibility rule (i.e., the EEA of age 62). First, I restrict samples to those who have participated in the HRS survey until age 64 or above (e.g., at least one post-treatment response) to address potential endogeneity from mortality around EEA and/or immigrant out-migration (Abramitzky et al., 2014; Fitzpatrick & Moore, 2018).[26] Second, this sample is further limited to parents who are 59–64 years old to cover 35 months before and 35 months after the month of one's 62nd birthday. A 35-month window can isolate the effects of the earliest eligible age (age 62) from those of the full retirement age (age 65) for Social Security and other federal and state programs. The final sample contains 50,260 observations.[27]

Variables

This study primarily examines four outcomes: the likelihood of downstream (parent-to-child) financial transfer, the likelihood of upstream (child-to-parent) financial transfer, the total amount of downstream transfer, and the total amount of upstream transfer. Transfer amounts are measured in U.S. dollars and are CPI-adjusted based on the 2018-year value. I do not examine the

[26] Attrition-induced sample bias can reduce the similarity between control and treatment groups. Specifically, Fitzpatrick & Moore (2018) showed that aggregate mortality increased by 1.5% within one month after the EEA. Abramitzky et al. (2014) found that immigrants with lower earnings (e.g., elderly retirees) had a higher propensity to leave the U.S.

[27] The main sample consists of parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding three months around age 62). More precisely, the main sample is limited to parents aged from 62 years and 5 months to 64 years and 12 months (i.e., posttest group) and from 59 years and 2 months to 61 years and 9 months (i.e., pretest group).

logged amount of transfers here; doing so would yield an insufficient sample size and associated biases, especially for an RDD.

The primary variable of interest is the earliest eligible age (EEA) threshold for Social Security, which is currently age 62. A dichotomous variable equal to 1 if parental age is above the EEA (and 0 otherwise), is employed to compare changes before and after crossing this threshold. This study utilizes the age in months, which can provide more sufficient variation (e.g., bandwidths) in RDD than the age in years found in the public-use HRS. I choose a local linear regression because high-order polynomials can lead to severe approximation errors in RDDs due to overfitting (Gelman & Imbens, 2019; Skovron & Titiunik, 2015). In the robustness check section, I experiment with second-order and third-order polynomial forms to investigate the age profile of intergenerational transfers.

For subgroup analyses, an immigrant family is denoted by a dichotomous variable equal to 1 if at least one parent is foreign-born (and 0 otherwise): a family with one U.S.-born parent and one foreign-born parent is classified as an immigrant family.

5. Analytic strategy

Regression discontinuity design

This study employs a regression discontinuity design (an RDD) using age as the assignment variable because the Social Security program has an age-related eligibility threshold (Fitzpatrick & Moore, 2018; Kim & Koh, 2020; Smythe, 2019). The analytic approach includes two processes: (i) a regression discontinuity estimation using the age threshold (age 62) to determine the effects of Social Security on intergenerational transfers; and (ii) a subgroup-based regression discontinuity

estimation to investigate immigrant-native differences in identified effects. For the former, I use an RDD to compare the transfer decisions of respondents below and above age 62. Parent-to-child transfer outcomes are examined first with:

$$Y_{ioa} = \beta_0 + \beta_1 * f(age_i - c) + \beta_2 * Treat_i + \delta' X_{ioa} + \varepsilon_{ioa}\,, \quad (1)$$

where Y_{ioa} denotes the likelihood (or amount) of financial transfers from a parent (i) at age (a) to a child (o) in the same family. The cut-off age (c) is 62, the EEA for Social Security. $f(age_i - c)$ is a smooth function between outcomes and age. $Treat_i$ is a dummy variable equal to 1 if the parent is over the cut-off age and 0 otherwise. X_{ioa} is a vector of demographic characteristics of the parent (i) and child (o) at parental age (a), similar to those in Papers 1 and 2. Parent characteristics include educational attainment, number of children, marital status, race and ethnicity, employment status, household income, and wealth. Child characteristics cover marital status, gender, educational attainment, employment status, number of children, and household income. The coefficient of interest is β_2, indicating a discontinuous change in transfer decisions at the cut-off age. The current study estimates the effects of being *eligible* to receive Social Security, an intent-to-treat effect. Robust standard errors are clustered at the family (parent) level to account for individual correlation across families.

Next, I analyze child-to-parent transfer outcomes using models similar to Equation (1). In this analysis, Y_{ioa} denotes the likelihood (or amount) of financial transfers from a child (o) to a parent (i) at parental age (a). All other covariates are the same as in Equation (1).

Notably, the current study estimates program effects while excluding individuals from interviews conducted within 3 months before and after the age threshold (also called Donut-hole RDD) to address potential biases following Barreca et al. (2016) and Kim and Koh (2020). Because

the age threshold is public knowledge, people may alter their transfer behavior under the expectation of soon reaching Social Security eligibility, otherwise known as anticipation effects (Lee & Lemieux, 2010). Additionally, the effects of Social Security on intergenerational transfer behaviors may be lagged because altering resource distribution patterns across generations (i.e., intergenerational transfers) can require some time (Kim & Koh, 2020). Figure 3.1 in the result section illustrates these possible biases from anticipation and lagged effects: transfer probabilities sharply change just around the cut-off age.[28] A donut-hole RDD is thus implemented in the primary analysis while testing alternative donut-hole sizes (i.e., the numbers of excluded months).

Subgroup regression discontinuity design

I further conduct subgroup analyses to discern differences between immigrant and native-born families. Prior studies carried out subgroup analyses using separate subset samples, which may be problematic (Mukherjee, 2022; Smythe, 2019). This study employs a difference-in-regression-discontinuities (DRD) strategy that combines an RDD approach with the difference-in-differences method (Grembi et al., 2016; Hong et al., 2019). This strategy is conceptually based on a subgroup indicator and an interaction term for the treatment indicator and thus addressing pre-existing differences among subgroups. I compare immigrants and natives within the 35-month bandwidth around the cut-off age of 62, in the following regression model for parent-to-child transfers:

[28] After excluding observations near the cut-off age, the fitted line exhibits smoother patterns compared to the one in Figure 3.1. Barreca et al. (2016) noted that this type of non-random accumulation can introduce bias.

$$Y^1{}_{ioa} = \beta^1{}_0 + \beta^1{}_1 f(age_i - c) + Immi_i * \left(\beta^1{}_2 + \beta^1{}_3 f(age_i - c)\right) + Treat_i * [\beta^1{}_4 + \beta^1{}_5 f(age_i - c) + Immi_i * \left(\beta^1{}_6 + \beta^1{}_7 f(age_i - c)\right)] + \delta^1 X_{ioa} + \varepsilon^1{}_{ioa} \quad (2)$$

where $Y^1{}_{ioa}$ denotes the likelihood (or amount) of financial transfers from a parent (i) at age (a) to a child (o) in the same family. $Immi_i$ denotes a binary variable equal to 1 if a parent's household is an immigrant family and 0 otherwise. Definitions of all other variables are identical to those in Equation (1). The coefficient $\beta^1{}_6$ is the DRD estimator and identifies the treatment effect: differences between immigrants and natives at the cut-off age. Next, I analyze child-to-parent transfers using models similar to Equation (2): $Y^1{}_{ioa}$ denotes the likelihood (or amount) of financial transfers from a child (o) to a parent (i) at parental age (a); all other covariates are the same as in Equation (2).

Some scholars have argued that this difference-in-regression-discontinuities (DRD) approach may be problematic in an RDD, except when the relationship between an outcome and the assignment (running) variable is consistent across subgroups (Carril et al., 2019).[29] Even though models allow for separate slopes by each subgroup, other observable characteristics may differ significantly across subgroups, leading to selection biases (Carril et al., 2019).

This study thus additionally employs a propensity score weighting method developed by Carril et al. (2019) to check the robustness of DRD estimates. This approach balances covariates around the threshold. Observations in each subgroup are weighted by the inverse of their conditional probabilities of belonging to that subgroup (Abadie, 2021; Boatman et al., 2022; Gulzar et al., 2021; Sánchez, 2022).[30] In this analysis, the empirical specification is the same as in

[29] For instance, slope estimates inevitably lie between the actual slope parameters, as ordinary least squares (OLS) regressions seek to minimize deviations from the regression line across subgroups (see the Carril et al. (2019) for more details).
[30] Conducting the RDD analysis independently within each weighted subgroup helps eliminate potential confounding differences arising from other observable factors that may systematically differ across (unweighted) subgroups.

Equation 1, although the sample is limited to each "weighted" subgroup (e.g., immigrants vs. native-born). I present the estimated effects for each subgroup and test the statistical significance of between-group differences.

Robustness checks

To verify the primary results' robustness, I estimate local nonparametric regressions (Calonico et al., 2014, 2015, 2017, 2019). Some scholars have contended that parametric methods in primary analysis can be problematic. First, the bandwidth can be chosen arbitrarily; second, the effects of the misspecification error are erroneously overlooked (Bartalotti & Brummet, 2017; Cattaneo et al., 2017). To address these issues, Calonico et al. (2014, 2015, 2017, 2019) developed a robust bias-adjusted inference method. For instance, their strategy provides a data-driven bandwidth selection process and removes first-order misspecification bias in the mean squared error (MSE) optimal RDD estimator. If the parametric method used in the primary analysis and this nonparametric method yield similar estimates, then my results can be considered relatively robust.

Specifically, I employ a widely recommended setting proposed by Calonico et al. (2014) and Cattaneo et al. (2017), which includes a local linear specification, a triangular kernel, and cluster-robust bias-corrected inference for confidence intervals. I test two types of bandwidths: (i) a fixed 35-month bandwidth, as in the primary analysis, and (ii) a data-driven selected bandwidth within a 35-month range.[31]

[31] When setting bandwidth ranges, I opt for a range within 35 months. Without this constraint, it becomes challenging to exclude possible biases due to the receipt of other state programs eligible at age 65. However, in this case, the effect sizes based on a data-driven selected bandwidth within a 35-month range can be larger (or smaller) than those based on a fixed-35month bandwidth, as this bandwidth becomes narrower than a fixed 35-month bandwidth.

6. Descriptive statistics

The descriptive statistics in Table 3.1 show three features. First, immigrants are less likely to receive Social Security benefits than the natives (Panel 3). This could be because they might have worked in formal jobs in the U.S. for less than 10 years, impacting their eligibility. Second, as in Papers 1 and 2, immigrant parents are more likely to receive money from their children and less likely to send them money in comparison to natives. The average amounts of immigrants' parent-to-child and child-to-parent transfers exceed those of natives (Panels 1 and 2). Third, immigrant families are socioeconomically vulnerable; they have less income and wealth, fewer years of education, and a weaker employment status than native families (Panels 4 and 5).

Table 3.2 contextualizes the relationships between transfer decisions and age 62 (the EEA) by comparing transfer outcomes between individuals before and after this age threshold. The overall likelihood and amounts of parent-to-child and child-to-parent transfers are higher for parents older than 62 versus those younger than 62 (Panels 1 and 2). However, such effects and corresponding magnitude differ by immigration status: differences in parent-to-child transfers between those below and above age 62 are larger for natives than for immigrants, whereas those in child-to-parent transfers are larger for immigrants than for natives.

These cross-sectional descriptive comparisons in Table 3.2 do not control for immigrant–native variation in demographics in Table 3.1. Such systematic differences also can confound subgroup-specific estimations (Carril et al., 2018). I thus examine whether transfer estimates persist after controlling for these differences in the corresponding section.

7. Results

1) Preliminary analysis: Effects of the EEA on transfers

Table 3.3 presents regression discontinuity estimates pertaining to the EEA's influence on transfer decisions. Column 1 lists estimates from the main model with a 3-month donut hole. Columns 2–4 show estimates with different donut holes to check biases from anticipation and lagged effects. Columns 5–6 present estimates from non-parametric models that address possible misspecification biases in parametric models.

Column 1 reveals three primary findings. First, the probability of parent-to-child transfers increases by 2% at the EEA in the main model. No statistically significant discontinuity applies to child-to-parent transfer probability at the 95% confidence level ($p < 0.05$). Transfer amounts also do not show significant estimated discontinuities at the EEA. These trends are similar to those of Mukherjee (2022). Findings suggest that older parents are more likely to send money to their children at the EEA; Social Security recipients may partially pass their benefits on to their adult children.[32]

The results using different donut holes imply biases from anticipation or lagged effects (Columns 2 to 4). If biases exist, then estimates can be expected to rise as the donut-hole size increases (Kim & Koh, 2020). In Panel 1-1, estimates of parent-to-child transfer probability incrementally increase as the size of donut holes become larger. Figure 3.1 depicts graphical evidence of these biases: transfer probabilities increase immediately before the cut-off age and sharply drop a few months after the cut-off age. The main model in Column 1 may indeed provide relatively accurate estimates that address such biases.

[32] The graphical evidence is provided in Figure 3.2.

Lastly, estimates from nonparametric models demonstrate directions and statistical significance of estimates comparable to those from the parametric models. Point estimates with the same 35-month bandwidth are nearly identical to those for the main model (Column 5). Results with data-driven MSE-optimal bandwidths show a similar or larger effect (which might be due to narrow bandwidths) (Column 6). These relatively consistent results imply that misspecification biases could accompany the parametric approach (as shown in varying effect sizes) but are not critical in this analysis.

In summary, older parents are more likely to send money to their children following the Social Security EEA. This suggests that Social Security for older parents also financially help the next generation, their adult children. Yet non-significant estimates of child-to-parent transfers in this section do not offer sufficient evidence for the alleviating role of Social Security in support burdens of adult-children, and transfer motivations. Some recognized biases are addressed through alternative models, which do not substantially confound the main findings.

2) Immigrant–native differences in the effects of the EEA on transfers

Differences between immigrants and natives

Tables 3.4 and 3.5 outline differences in transfer decisions between immigrants and natives at the EEA. Table 3.4 contains estimates from the difference-in-regression-discontinuity (DRD) model. Table 3.5 presents estimates from the regression discontinuity model in the preceding section for each subgroup, weighted by conditional probabilities of belonging to that subgroup (Carril et al., 2018). Consistent results across these two models would indicate relatively robust findings.

The estimates based on DRD in Table 3.4 reveal that the difference between immigrants and natives at the EEA is only evident in the child-to-parent transfer amount. Immigrants' children are likely to send $245 less to their parents than comparable native children at the EEA (Column 1, Panel 2-2). The coefficient for the combined estimate (Treat and Treat*Immigrant) is statistically significant across all models at the 95% confidence level. Notably, U.S.-born families do not exhibit significant discontinuity in their child-to-parent transfer amount in response to the EEA. Other transfer outcomes do not show significant immigrant–native differences. These trends are fairly similar across non-parametric models and models with different donut holes (Columns 2 to 6).

The estimates for subgroup-based RDDs in Table 3.5 are similar to those in Table 3.4.[33] Immigrants' children send $221 less to their parents corresponding to the EEA; children in U.S.-born families do not display significant changes, similar to the DRD estimates in Table 3.4 (Column 1, Panel 2-2). Immigrant–native difference in child-to-parent transfer amount (i.e., $251) is also comparable to the DRD estimates (i.e., $245) and statistically significant at the 95% confidence level. There are also no significant immigrant-native differences in other transfer outcomes. Again, coefficients' directions and significances also remain consistent across non-parametric models and models with various donut holes. The constancy of estimates across both models (i.e., DRD in Table 3.4 and subgroup-based RDDs in Table 3.5) conveys the relative robustness of observed immigrant–native differences.

In brief, these findings highlight an important difference in transfer behaviors in immigrant versus native households. At the Social Security EEA, immigrant parents experience a decline in transfer amounts from their children via crowding-out effect, whereas there is no such change in

[33] The graphical evidence of subgroup-based RDDs is provided in Figure 3.3.

the case of native parents. This finding implies that immigrant families' transfer behaviors might be substantially driven by altruistic motivations (Barro, 1974; Becker, 1974). The immigrant-native difference also supports the solidarity hypothesis, which posits stronger altruistic cohesion among immigrant families than native families (Dumon, 1989; Nauck, 2001).

Heterogeneity among immigrants: The role of Social Security eligibility

I also explore an institutional factor influencing immigrants' transfer behaviors and the associated immigrant-native differences. If transfer decisions between eligible and ineligible immigrants do not differ at the EEA, then eligibility may not be responsible for observed immigrant–native differences in transfer decisions in the prior section. Specifically, I compare transfer decisions among immigrants at the EEA: (i) immigrants who are eligible for Social Security (i.e., more than 10 years of U.S. work experience) and those who are ineligible, and (ii) male and female immigrants. One potential problem with this analysis is that the work experience history of immigrants may be endogenous to intergenerational transfers; those not expecting support from their children may increase their work quarters to gain eligibility for Social Security. In an additional analysis, I compare male immigrants to female immigrants, who generally have a lower employment probability.[34] I use subgroup-based RDDs for straightforward comparisons.[35]

Estimates in Table 3.6 present that immigrant's transfer behaviors at the EEA primarily originate from eligible (or male) immigrants compared to ineligible ones who cannot receive Social Security benefits (or female immigrants). For instance, children of eligible immigrants

[34] In this study, a smaller proportion of female immigrants (72%) have a 10-year U.S. work experience compared to male immigrants (92%) and native-born females (90%). These differences may be even larger if I consider whether work experience is in a formal sector, but HRS data does not provide this information.
[35] The results of the difference-in-regression-discontinuity (DRD) model also show consistent results (in Appendix Table A3.1).

decrease child-to-parent transfer amount by $307 at the EEA, while ineligible immigrants do not have significant changes (Column A, Panel 2-2). This eligible-ineligible immigrant difference is statistically significant at the 99% confidence level. Similarly, male immigrants demonstrate a significant and larger effect size than female immigrants (Column B). These results suggest that Social Security eligibility (i.e., 10 years of work experience in the U.S.) is likely to be a predictor of immigrants' transfer decisions and thus may account for corresponding immigrant–native differences in the prior section.

3) Intergenerational redistributive effects of the Social Security

In this section, I examine transfer decisions at the EEA based on the income level of adult children to explore the redistributive effects of Social Security. If a decline in child-to-parent transfer is more significant and larger for children with low-income families, then Social Security may partially entail intergenerational redistributive effects via intergenerational transfers, preventing the transmission of poverty. HRS does not provide sufficient information on poverty status but does offer categorical income for children's households. I thus establish two subgroups (e.g., more or less than $35,000 annual earnings) that closely align with the federal poverty threshold.[36] I also employ subgroup-based RDDs for simple comparison.[37]

Results in Table 3.7 show that transfer decisions change at the EEA, particularly for families with low-income children. Specifically, older parents are more likely to transfer to their children at the EEA when children's income levels are low, for both immigrant and native families

[36] The 2018 federal poverty thresholds for a family of four and larger range from $25,750 to $43,430 (U.S. Census Bureau, 2019). HRS provides four categorical annual income brackets for children's household: under $10,000, $10,000 to $35,000, $35,000 to $70,000, and over $70,000. Therefore, $35,000 in HRS can serve as the threshold relatively closest to the federal poverty threshold.
[37] The difference-in-regression-discontinuity (DRD) estimates also presents consistent results (see the Appendix Table A3.2.).

(Columns 2 and 5, Panel 1-1). Furthermore, immigrants' children decrease child-to-parent transfers at the EEA when their income levels are low, while native-born and other immigrant groups do not exhibit significant changes (Column 5, Panel 2).

These findings indicate that families with relatively low-income children underpin the baseline results shown in Tables 3.3 to 3.5. For instance, the Social Security of immigrant parents significantly reduces the financial support burden for their children in low-income. As in Table 3.1, immigrant families generally have fewer private economic resources and are also less covered by public transfer than natives. Given these results, this redistributive effect of Social Security could mitigate the intergenerational transmission of poverty, by displacing familial security with Social Security.

8. Validity tests of RDD

1) RDD identification assumptions

The RDD approach is based on three identification assumptions (Cattaneo et al., 2017; Skovron & Titiunik, 2015). First, there should be no additional source of discontinuity at the EEA other than that caused by the intervention (i.e., Social Security). The age of eligibility for most public transfer programs geared towards older adults (e.g., Supplemental Security Income, Medicare) is 65. Second, a respondent should not manipulate the assignment variable. Intuitively, biological age (the EEA) in this study is unlikely to be subject to manipulation. Estimated results from the McCrary test also verify the absence of age-based manipulation; no significant difference is observed in the estimated densities of pretest and posttest units on either side of the EEA at the

99% confidence level (i.e., $p = 0.594$).[38] Lastly, changes in covariates around the cut-off should not cause any discontinuous changes in outcome variables. To assess this assumption, I employ the same RDD with each covariate as a new outcome, to examine if individual's characteristics are balanced around the cut-off. Table 3.8 demonstrates that covariates generally do not show discontinuous changes at the cut-off at the 99% confidence level.

2) Effect of the EEA on Social Security benefit receipt

My analysis rests on the assumption that a substantial number of older parents actually receive Social Security benefits at age 62 (EEA). I test if this assumption is valid, and the estimated results presented in Table 3.9 confirm that Social Security receipt increases at the EEA by 25.1%, suggesting an actual increase in income of older parents (i.e., Social Security benefit).[39] Further, immigrants are less likely to receive Social Security compared to native-born counterparts at the EEA (Columns 2 and 3).

These results are consistent with previous research indicating immigrants are less covered by Social Security than natives, which may be due to weaker employment histories combined with the current Social Security eligibility rule (i.e., 10 years of U.S. work experience) (Favreault & Nichols, 2012; Sevak & Schmidt, 2014). Such lower rates of Social Security receipt among immigrants also offer larger estimates relative to natives in their transfer decisions and associated immigrant–native differences in terms of average treatment effects on the treated (ATT), compared to the intent-to-treat (ITT) estimates presented in previous sections.[40]

[38] McCrary (2008) introduced a falsification method for the RDD approach, taking discontinuity in the assignment variable's density near the cut-off as evidence of manipulation. This test compares estimated densities of control and treatment units, originally using local polynomial techniques for smoothed histogram estimators.
[39] This proportion is fairly reliable, as official statistics show that approximately 29% of those who can claim Social Security actually receive them at the EEA (CRS, 2022).
[40] All estimates in prior sections present the intent-to-treat (ITT) effects. I divided the estimates in prior sections by change in the likelihood of receiving Social Security (of each subgroup) at the EEA, to calculate average treatment effects on the treated (ATT).

9. Additional robustness checks

To test findings' validity, I conduct two more robustness checks. I first utilize several age-cutoff points as falsification tests. If the main results are valid, then estimates from these falsification tests should differ from those in the main findings. Estimated results in Appendix Tables A3.3 to A3.6 indicate that the significance and direction of coefficients on treatment are not comparable to those in the main results in Tables 3.3 to 3.5.[41] As such, the effects in the main results appear to relatively accurately capture the impact of Social Security on intergenerational transfers.

Next, I test age-profiles of intergenerational transfers with different polynomial orders. Increasing the polynomial's order typically enhances the precision of the approximation, also with increased variability for a given bandwidth (Skovron & Titiunik, 2015); however, scholars pointed out that high-order polynomials can lead to severe approximation errors due to overfitting (Gelman & Imbens, 2019). I experiment with second-order and third-order polynomials of the age profile of financial transfers in Appendix Tables A3.7 to A3.8. Estimates show that the direction and significance of coefficients are consistent with those in the main results; effect sizes are slightly larger than the main estimates.[42] There are no substantial differences in R-squared across models with different polynomial orders. I thus prefer to use the reduced form function (i.e., linear age profiles of transfers) in the main analyses.

For instance, the estimated immigrant–native difference per the ATT is approximately $1,002 (=-251.580/0.251) based on subgroup-based RDDs. If Social Security receipt rates were separately applied to immigrant and native subgroups, then the immigrant–native difference would be $1,382 (= (29.994/0.274) - (-221.586/0.174)) —approximately 38% larger than prior ATT estimates. The immigrant–native differences in transfer behaviors could be even more pronounced.

[41] These trends remain consistent across nonparametric models and models with various donut holes.

[42] For a straightforward comparison, the main estimates from the first-order equation are also provided in Appendix Table A3.9.

10. Discussion and Conclusion

This paper examines the impact of the U.S. Social Security program on intergenerational transfers and the corresponding differences between immigrants and natives using HRS data from 1996 to 2018 years. I employ several RDD models using the EEA cut-off (age 62) to address biases from individual behaviors and model specification concerns. Findings expand and build up the literature on how public transfers affect private transfers in the U.S. context. Preliminary analyses revealed that Social Security eligibility (i.e., the EEA) was positively associated with parent-to-child transfer probability. Results for child-to-parent transfers did not provide strong evidence for a role of Social Security in children's support burden and related transfer motivations. These results were consistent with those observed previously (i.e., Mukherjee, 2022) while using data from a wider range of birth cohorts. Relatively consistent results across models verified that potential biases were less critical, at least in my estimation.

I then tested the hypothesis that the impact of Social Security on intergenerational transfers differs by immigration status. While preliminary analyses for the entire sample did not reveal significant changes in child-to-parent transfers, subgroup analyses showed that children in immigrant families reduced child-to-parent transfer amounts at the EEA (i.e., a crowding-out effect) while children in U.S.-born families did not. This highlights the role of Social Security in alleviating the financial support burden on children of immigrants; transfer behaviors of immigrant families thus appear to stem from altruistic motivations (Barro, 1974; Becker, 1974). The significant immigrant-native differences also support the solidarity hypothesis, which posits stronger altruistic cohesion among immigrant families (Dumon, 1989; Nauck, 2001). In addition to this theoretical explanation, the current Social Security eligibility rule (i.e., a 10-year U.S. work

experience) was a likely predictor of immigrants' transfer decisions, which ties into the corresponding immigrant–native differences.

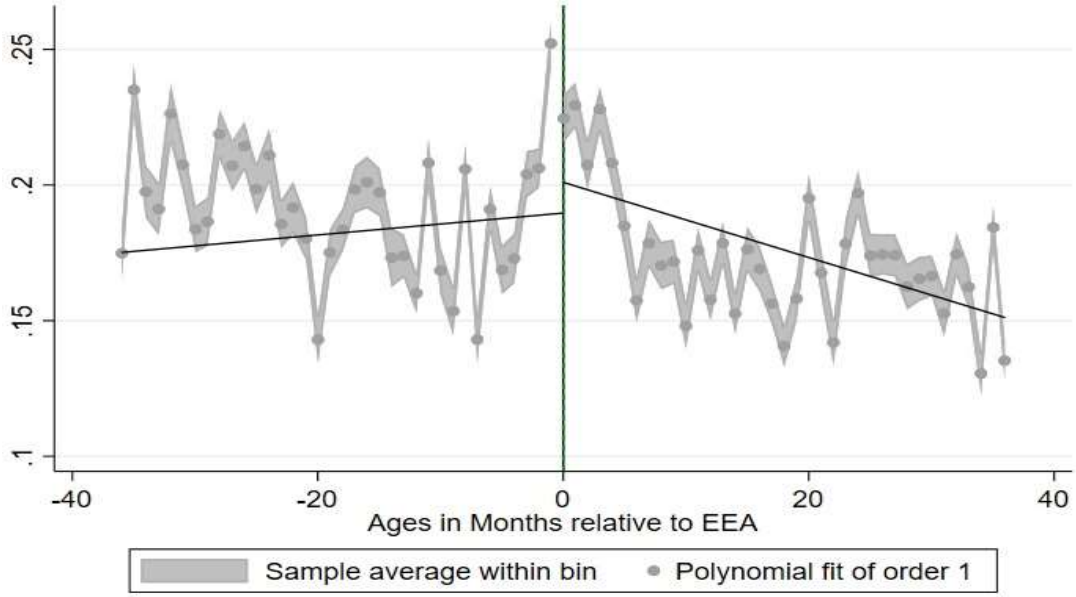
I further found the intergenerational redistributive effect of the Social Security program. The Social Security EEA significantly reduced adult children's financial support burden, particularly for low-income immigrant children. This suggests that Social Security may contribute to reducing the intergenerational transmission of poverty, by displacing familial security with Social Security.

This study highlights two policy-related themes. First, understanding the role of intergenerational transfers in Social Security can improve the design of Social Security and its reform (CRS, 2022). Parents were more likely to send money to their children in response to Social Security receipts, causing the effect of Social Security to be slighter than expected. In addition, if benefit levels are reduced as proposed in several Social Security reform scenarios, these impacts will be transmitted to children through familial transfers because these children will receive less money from their older parents.

Second, current Social Security eligibility rules and reform scenarios need to be reevaluated, as they may disproportionately exacerbate the financial (support) burden of immigrant families compared with U.S.-born families. Older immigrant parents are less covered by Social Security under today's eligibility rules due to having weaker work histories than their native counterparts (Favreault & Nichols, 2012; Sevak & Schmidt, 2014). Children of immigrants are instead more likely to support their older parents than natives. The current study also found that Social Security alleviates support burdens of children in immigrant families through the crowding-out effect, different from insignificant changes among comparable children in native-born families.

Social Security reforms with reduced benefits and periods may indeed amplify this support burden for the next generation, disproportionately affecting immigrants.

Figure 3.1. Age profiles of parent-to-child transfer probability: Without a donut-hole



Notes: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years, including all months around age 62 (i.e., without a donut-hole). The outcome is parent-to-child transfer probability. The horizontal axis represents distances from the month of the 62nd birthday. Dots indicate the averages of the outcome variable in each age in months. Black lines represent a local linear regression fit separately on either side of zero using the uniform kernel. The shaded area indicates 95% confidence intervals of the local linear regressions.

Table 3.1. Descriptive statistics by immigration status

	(A) Native (U.S.-born) family	(B) Immigrant family	(C) Difference
Panel 1. Transfer probability (%)			
Parent-to-child transfer	17.02	13.79	-3.23*
Child-to-parent transfer	2.00	4.01	2.01*
Panel 2. Transfer amount ($)			
Parent-to-child transfer	1215.68	1522.01	306.33*
Child-to-parent transfer	60.20	351.01	290.81*
Panel 3. Social Security (%)			
Social Security benefit receipt	19.50	12.22	-7.28*
Social Security eligible (i.e., a 10-year work in the U.S.)	93.85	84.45	-9.40*
Panel 4. Child's characteristics			
Annual household income ($)	54,669	44,576	-10,093*
Years of education	13.39	12.99	-0.40*
Married	56.63	58.79	2.16*
Currently in schools	6.39	7.77	1.38*
Number of kids	1.65	1.56	-0.09
Gender (Male)	50.07	49.57	-0.50*
Employed	83.05	81.51	-1.54*
Panel 5. Parent's characteristics			
Annual household income ($)	76,238	62,717	-13,521*
Annual household wealth ($)	428,604	342,879	-85,725*
Hispanic	7.05	60.13	53.08*
Non-white	32.39	44.79	12.40*
Years of education	12.38	10.05	-2.33*
Married	51.70	61.37	9.67*
Number of kids	4.23	4.70	0.47
Employed	56.65	56.23	-0.42*
Number of observations	42,733	7,527	

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding three months around age 62). Column (A) shows descriptive data for the U.S.-born (native) families, Column (B) for immigrant families. Column (C) lists the mean differences between native and immigrant groups (= Immigrant - Native). The numbers in each column represent the mean value for each variable. Asterisk (*) indicates that differences in mean values between immigrants and natives are statistically significant with 99% confidence level ($p<0.01$.). Data is sourced from HRS data from 1996 to 2018 years.

Table 3.2. Relationships between the Social Security EEA (age 62) and transfers

	(A) U.S.-born (Native) families			(B) Immigrant families		
	Before 62	After 62	Diff	Before 62	After 62	Diff
Panel 1. Transfer probability (%)						
Parent-to-child transfer	15.98	18.18	2.20*	13.10	14.58	1.48*
Child-to-parent transfer	1.96	2.03	0.07	3.24	4.58	1.34*
Panel 2. Transfer amount ($)						
Parent-to-child transfer	1,139.08	1,301.62	162.54*	1,447.35	1,500.51	53.16*
Child-to-parent transfer	62.64	66.95	4.31*	348.19	354.11	5.92*
Number of observations	21,053	21,680		3,421	4,106	

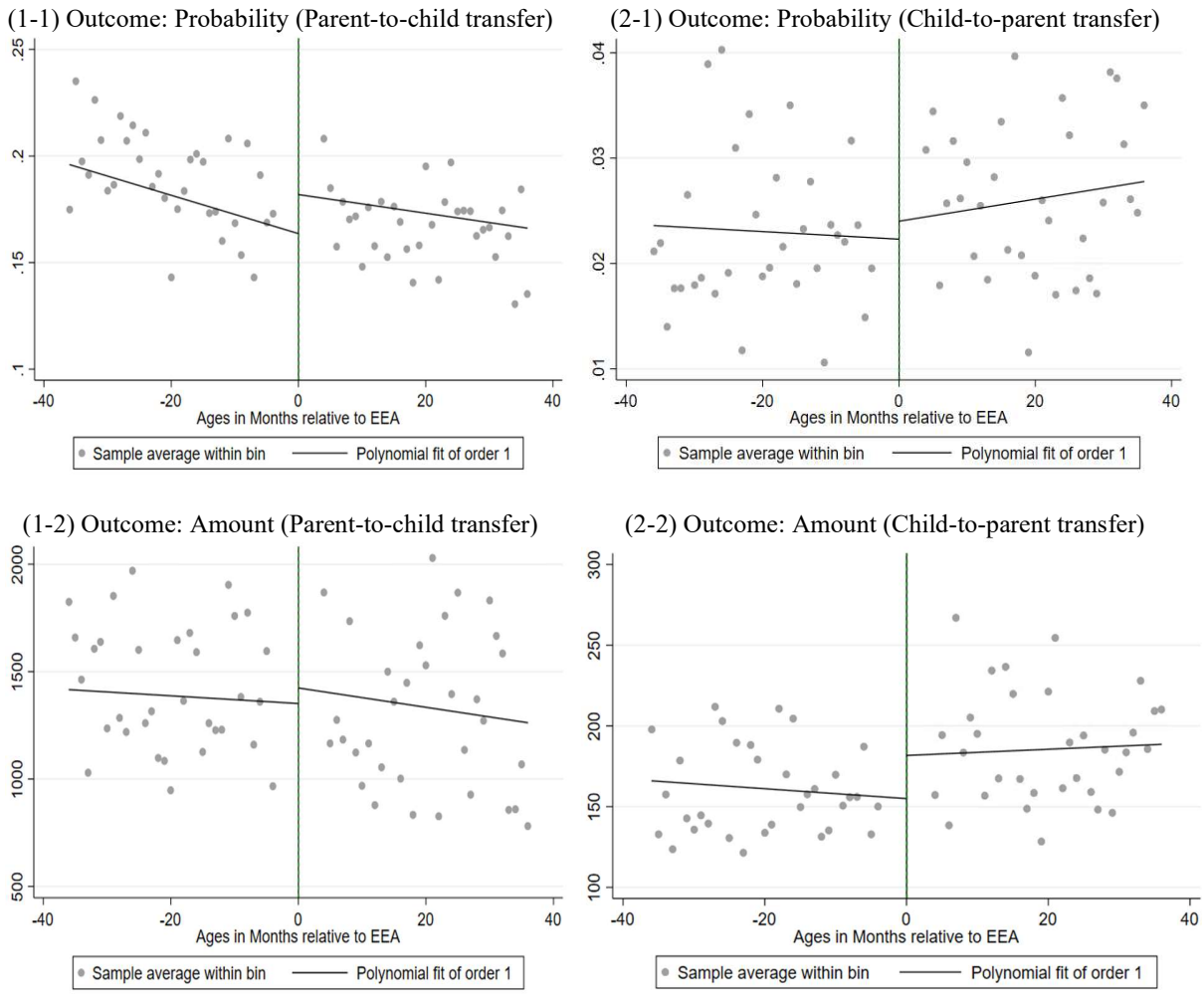
Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding three months around age 62). "Before 62" refers to a parent whose age is less than 62, the EEA; "After 62" refers to a parent whose age is 62 and more. The "Diff" column lists the mean probability (or amount) differences between Before 62 and After 62 groups (= After 62 – Before 62). Column (A) shows descriptive data for the U.S.-born (native) families, Column (B) for immigrant families. Asterisk (*) indicates that differences in mean values between immigrant and native are statistically significant with 99% confidence level ($p<0.01$.). Data is sourced from HRS data from 1996 to 2018 years.

Table 3.3. RDD estimates of the impact of the EEA on intergenerational transfers

	Parametric RDD				Non-parametric RDD	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1. Parent-to-Child transfer						
Panel 1-1. Probability						
Treat	0.020**	0.017**	0.016**	0.010	0.018**	0.050**
	(0.009)	(0.007)	(0.007)	(0.006)	(0.009)	(0.025)
Panel 1-2. Amount						
Treat	72.464	60.345	47.813	18.200	56.947	116.351
	(154.860)	(139.562)	(130.616)	(116.749)	(79.101)	(112.122)
Panel 2. Child-to-Parent transfer						
Panel 2-1. Probability						
Treat	0.004	0.003	0.003	0.003	0.005	0.015*
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.009)
Panel 2-2. Amount						
Treat	42.373	14.959	13.823	3.011	19.915	44.271
	(41.796)	(37.018)	(29.150)	(22.285)	(44.870)	(53.502)
Donut hole size	3 months	2 months	1 month	0 month	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months	35 months	MSE-optimal
Num. of observations	50,260	51,808	53,375	55,766	50,260	

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (e.g., a 35-month age bandwidth excluding some months around age 62). "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Each panel pertains to a specific transfer outcome. The numbers in each cell represent regression discontinuity estimates for each transfer outcome, obtained from separate regression. Column 1 shows the main estimates using a 3-month donut hole. Columns 2 to 4 represent estimates based on different donut-hole sizes. Columns 5 and 6 provide estimates from nonparametric models. Other covariates are not listed in the table. The sample size in Column 6 varies by transfer outcomes due to their corresponding data-driven bandwidths. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Figure 3.2. Graphical evidence: RDD estimates of the impact of the EEA on intergenerational transfers



Notes: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding 3 months around age 62). The horizontal axis represents distance from the month of the 62nd birthday. Dots indicate the averages of the outcome variable in each age in month. Black lines represent a local linear regression fit separately on either side of zero using the uniform kernel. Shaded area indicates 95% confidence intervals of the local linear regressions.

Table 3.4. DRD estimates: immigrant-native differences in the impact of the EEA on transfers

	Parametric DRD				Non-parametric DRD	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1. Parent–to–Child transfer						
Panel 1-1. Probability						
Treat	0.019**	0.016**	0.016**	0.011	0.013*	0.035**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.017)
Treat * Immigrant	0.007	0.007	0.001	-0.006	-0.007	-0.007
	(0.006)	(0.007)	(0.007)	(0.006)	(0.016)	(0.041)
Immigrant	0.026*	0.024*	0.026**	0.030**	0.039***	0.039**
	(0.015)	(0.014)	(0.013)	(0.013)	(0.012)	(0.019)
Panel 1-2. Amount						
Treat	98.149	74.514	53.666	63.181	264.432	561.486
	(157.131)	(141.342)	(133.906)	(120.545)	(211.693)	(588.903)
Treat * Immigrant	-188.438	-105.365	-43.242	-299.689	-311.703	-679.337
	(552.168)	(493.318)	(445.449)	(392.820)	(871.691)	(740.887)
Immigrant	1,444.802***	1,319.217***	1,175.908***	1,185.578***	1,589.836**	2,163.723***
	(406.826)	(361.552)	(327.731)	(302.575)	(657.219)	(809.374)
Panel 2. Child–to–Parent transfer						
Panel 2-1. Probability						
Treat	0.001	0.002	0.003	0.003	0.003	0.018
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.012)
Treat * Immigrant	-0.006	-0.004	-0.003	-0.001	-0.005	-0.012
	(0.011)	(0.011)	(0.010)	(0.009)	(0.010)	(0.041)
Immigrant	0.024***	0.023***	0.020***	0.015**	0.016**	0.040*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.024)
Panel 2-2. Amount						
Treat	26.542	22.732	15.501	19.957	26.392	38.145
	(20.518)	(18.684)	(16.932)	(14.849)	(16.065)	(38.745)
Treat * Immigrant	-245.454***	-240.073***	-190.760**	-173.696**	-224.282***	-542.369**
	(84.155)	(86.818)	(78.310)	(68.513)	(77.946)	(266.862)
Immigrant	299.731***	299.649***	258.771***	225.519***	274.538***	573.211**
	(62.465)	(81.205)	(63.529)	(56.862)	(65.465)	(251.987)
Donut hole size	3 months	2 months	1 month	0 month	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months	35 months	MSE-optimal
Num. of observations	50,260	51,808	53,375	55,766	50,260	

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (e.g., a 35-month age bandwidth excluding some months around age 62). "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. "Immigrant" indicates a dummy variable indicating 1 if at least one parent is foreign-born (immigrant), otherwise 0. Each panel pertains to a specific transfer outcome. The numbers in each cell represent difference-in-regression-discontinuity estimates for each transfer outcome, obtained from separate regression. Column 1 shows main estimates using a 3-month donut hole. Columns 2 to 4 represent estimates based on different donut-hole sizes. Columns 5 and 6 provide estimates from nonparametric models. Other covariates are not listed in the table. The sample size in Column 6 varies by transfer outcomes due to their corresponding data-driven bandwidths. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Table 3.5. Subgroup-based RDDs: immigrant-native differences in the impact of the EEA on transfers

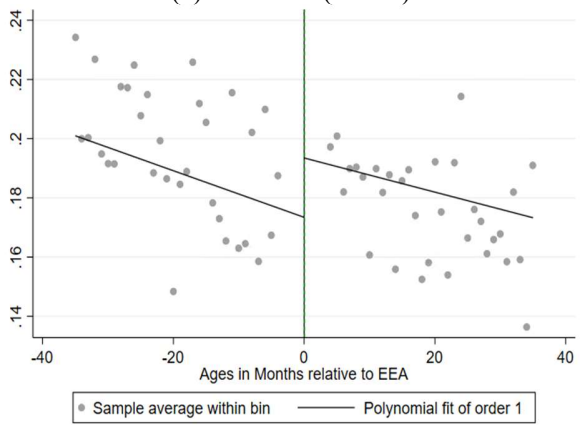
	Parametric RDD				Non-parametric RDD	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1. Parent–to–Child transfer						
Panel 1-1. Probability						
Natives (U.S-born)	0.020*	0.016**	0.016**	0.010	0.016*	0.044*
	(0.011)	(0.008)	(0.007)	(0.008)	(0.009)	(0.025)
n	42,733	44,046	45,384	47,453	42,733	21,998
Immigrants	0.018*	0.017*	0.015*	0.003	0.021*	0.094*
	(0.010)	(0.010)	(0.009)	(0.017)	(0.012)	(0.054)
n	7,527	7,762	7,991	8,313	7,527	3,122
Difference	-0.002	0.001	-0.001	-0.007	0.005	0.050
Panel 1-2. Amount						
Natives (U.S-born)	100.603	80.857	80.740	68.040	77.339	379.549
	(174.195)	(156.084)	(148.922)	(131.752)	(170.562)	(801.686)
n	42,733	44,046	45,384	47,453	42,733	15,997
Immigrants	-93.596	-161.880	-183.947	-391.370	-275.906	-885.945
	(1,312.878)	(1,181.343)	(1,099.295)	(950.894)	(885.099)	(909.594)
n	7,527	7,762	7,991	8,313	7,527	2,202
Difference	-194.199	-242.737	-264.687	-459.410	-353.245	-1,265.494
Panel 2. Child–to–Parent transfer						
Panel 2-1. Probability						
Natives (U.S-born)	0.004	0.005	0.005	0.004	0.008*	0.025
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.020)
n	42,733	44,046	45,384	47,453	42,733	20,112
Immigrants	-0.010	-0.013	-0.011	-0.011	-0.005	-0.003
	(0.014)	(0.018)	(0.016)	(0.015)	(0.013)	(0.028)
n	7,527	7,762	7,991	8,313	7,527	3,410
Difference	-0.014	-0.018	-0.016	-0.015	-0.013	-0.028
Panel 2-2. Amount						
Natives (U.S-born)	29.994	27.694	19.828	20.048	31.804	24.969
	(19.443)	(17.812)	(16.141)	(14.445)	(22.645)	(35.588)
n	42,733	44,046	45,384	47,453	42,733	19,213
Immigrants	-221.586***	-192.833**	-164.872**	-164.580**	-141.152**	-341.793**
	(82.359)	(96.841)	(86.445)	(77.265)	(72.160)	(143.476)
n	7,527	7,762	7,991	8,313	7,527	2,992
Difference	-251.580**	220.527*	-184.700*	-184.628*	-172.956*	-366.762**
Donut hole size	3 months	2 months	1 month	0 month	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months	35 months	MSE-optimal
Total num. of observation	50,260	51,808	53,375	55,766	50,260	

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (e.g., a 35-month age bandwidth excluding some months around age 62). "Natives" indicates a subsample for U.S-born families; "Immigrants" indicates a subsample for immigrant families. *n* indicates sample size of each subgroup. The "Difference" row lists differences in estimates between Natives and Immigrants groups (= Immigrants – Natives). Each panel pertains to a specific transfer outcome. The numbers in each cell represent regression discontinuity estimates for each transfer outcome and subgroup, obtained from separate regression. Column 1 shows main estimates using a 3-month donut hole. Columns 2 to 4 represent estimates based on different donut-hole sizes. Columns 5 and 6 provide estimates from nonparametric models. Covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup. Other covariates are not listed in the table. The sample size in Column 6 varies by transfer outcomes due to their corresponding data-driven bandwidths. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

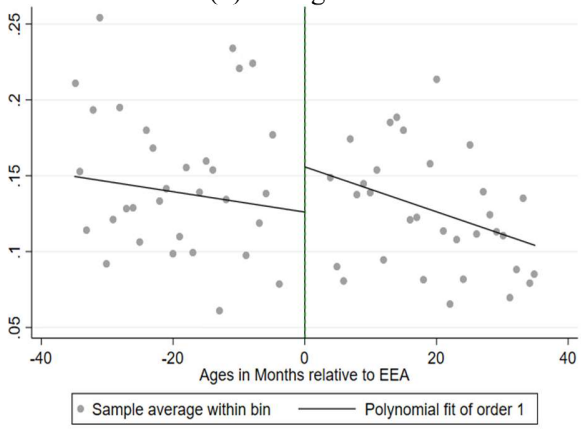
Figure 3.3. Graphical evidence: immigrant-native subgroup analysis

1-1. Outcome: Probability (Parent-to-child transfer)

(a) U.S-born (native)

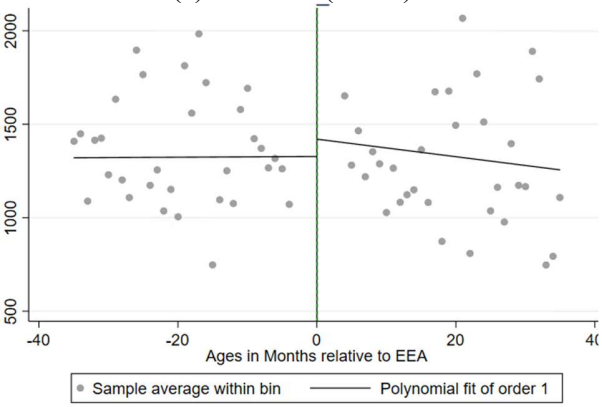


(b) Immigrant

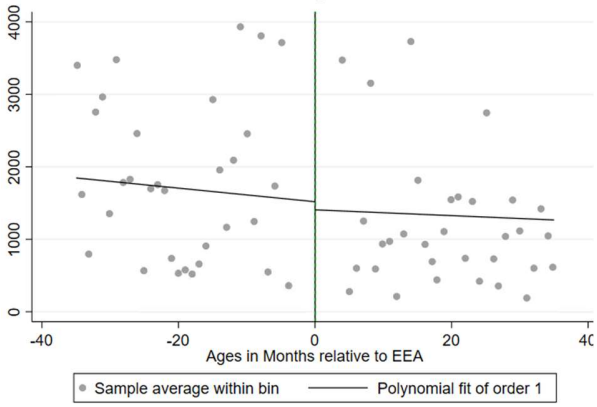


1-2. Outcome: Amount (Parent-to-child transfer)

(a) U.S-born (native)

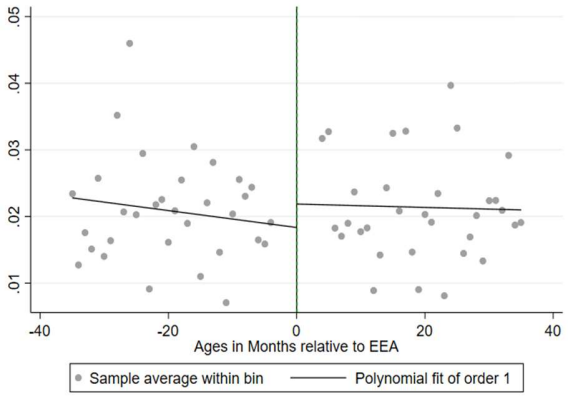


(b) Immigrant

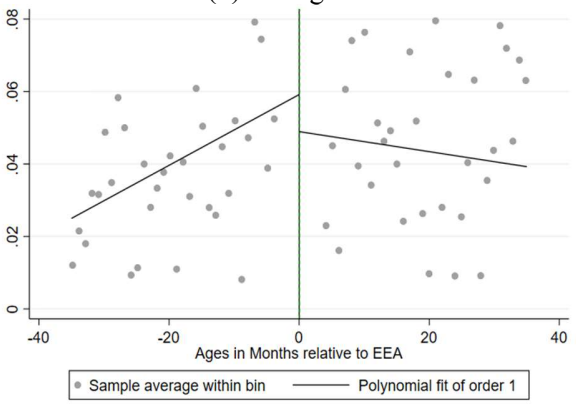


2-1. Outcome: Probability (Child-to-parent transfer)

(a) U.S-born (native)

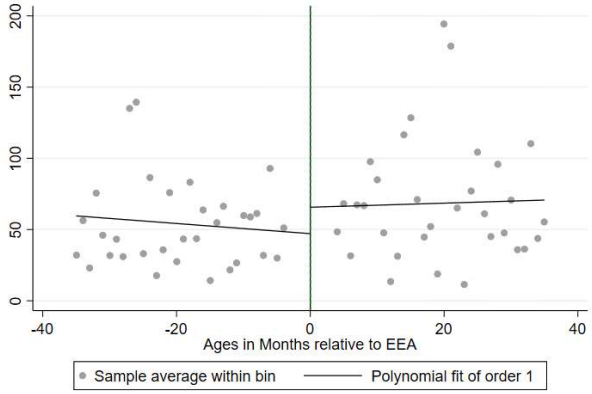


(b) Immigrant

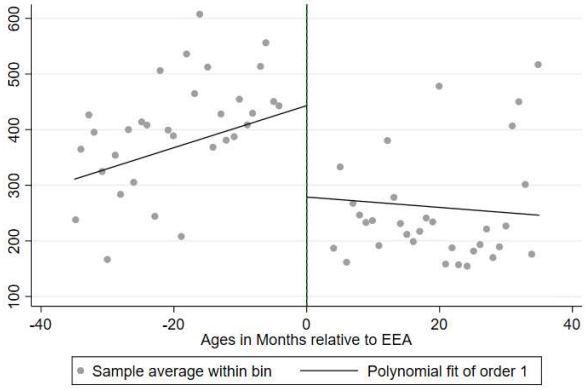


2-2. Outcome: Amount (Child-to-parent transfer)

(a) U.S-born (native)



(b) Immigrant



Notes: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years, excluding 3 months around age 62. "U.S-born (native)" indicates a subsample for U.S-born; "Immigrants" indicates a subsample for immigrant. The horizontal axis represents distance from the month of the 62nd birthday. Dots indicate the averages of the outcome variable in each age in month. Black lines represent a local linear regression fit separately on either side of zero using the uniform kernel. Shaded area indicates 95% confidence intervals of the local linear regressions.

Table 3.6. Subgroup analysis among immigrants, by Social Security eligibility and gender

	(A) Eligible-Ineligible immigrants			(B) Male-Female immigrants		
	(1) Ineligible	(2) Eligible	(3) Diff	(4) Female	(5) Male	(6) Diff
Panel 1. Parent-to-Child transfer						
Panel 1-1. Probability						
Treat	-0.011	0.040**	0.051*	0.015	0.027**	0.012*
	(0.022)	(0.020)		(0.010)	(0.012)	
Panel 1-2. Amount						
Treat	531.604	-386.217	-917.821	222.347	-268.845	-491.192
	(842.132)	(762.068)		(912.111)	(659.635)	
Panel 2. Child-to-Parent transfer						
Panel 2-1. Probability						
Treat	0.013	-0.013	-0.026	0.009	-0.016	-0.025
	(0.018)	(0.015)		(0.011)	(0.011)	
Panel 2-2. Amount						
Treat	484.194	-307.021***	-791.215***	31.842	-583.242***	-615.084***
	(314.413)	(103.680)		(167.237)	(191.883)	
Donut hole size	3 months	3 months		3 months	3 months	
Bandwidths	35 months	35 months		35 months	35 months	
Number of observations	377	7,150		3,004	4,523	

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding 3 months around age 62). "Ineligible" means a subsample for Social Security ineligible immigrants who do not have a 10-year U.S. work experience; "Eligible" indicates a subsample for Social Security eligible older immigrants who have a 10-year U.S. work experience. "Female" indicates a subsample for female immigrants; "Male" indicates a subsample for male immigrants. The "Diff" column lists differences in estimates between Ineligible (Female) and Eligible (Male) groups. Each panel pertains to a specific transfer outcome. The numbers in each cell represent regression discontinuity estimates for each transfer outcome and subgroup, obtained from separate regression. Covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Table 3.7. Subgroup analysis, by income level of adult children

	(A) U.S.-born (Native)			(B) Immigrant		
	(1) High-income (>35K)	(2) Low-income (<35K)	(3) Diff	(4) High-income (>35K)	(5) Low-income (<35K)	(6) Diff
Panel 1. Parent-to-Child transfer						
Panel 1-1. Probability						
Treat	-0.025	0.042***	0.067**	-0.016	0.067**	0.083**
	(0.018)	(0.014)		(0.017)	(0.032)	
Panel 1-2. Amount						
Treat	228.925	-51.950	-280.875	229.969	-315.882	-545.851
	(209.726)	(53.940)		(961.918)	(648.143)	
Panel 2. Child-to-Parent transfer						
Panel 2-1. Probability						
Treat	0.015	-0.011	-0.026	0.004	-0.018**	-0.022**
	(0.013)	(0.012)		(0.004)	(0.008)	
Panel 2-2. Amount						
Treat	37.331	23.528	-13.803	68.838	-323.102**	391.940**
	(28.711)	(20.425)		(45.534)	(161.505)	
Donut hole size	3 months	3 months		3 months	3 months	
Bandwidths	35 months	35 months		35 months	35 months	
Number of observations	23,050	19,683		2,966	4,561	

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding 3 months around age 62). Column (A) shows estimates for the U.S.-born (native) families, Column (B) for immigrant families. "High-income" refers to a subsample whose parental annual income is $35,000 or more; "Low-income" refers to a subsample whose parental annual income is less than $35,000. The “Diff” column lists differences in estimates between High-income and Low-income groups (=Low-income – High-income). Each panel pertains to a specific transfer outcome. “Treat” is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. The numbers in each cell represent regression discontinuity estimates for each transfer outcome and subgroup, obtained from separate regression. Covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Table 3.8. RDD estimates of the impact of the EEA on covariates

	(A) U.S.-born (Native)	(B) Immigrant	(C) Entire sample
Panel 1. Child's characteristics			
Household income	-0.015	0.040	-0.007
	(0.017)	(0.045)	(0.016)
Years of education	0.022	-0.082	0.007
	(0.040)	(0.116)	(0.039)
Married	-0.008	0.001	-0.007
	(0.009)	(0.022)	(0.008)
Currently in school	-0.007	-0.006	-0.007
	(0.005)	(0.014)	(0.005)
Number of kids	-0.006	-0.009*	-0.032
	(0.031)	(0.005)	(0.029)
Gender (Male)	-0.008	-0.006	-0.008
	(0.011)	(0.026)	(0.010)
Employed	0.009	-0.013	0.006
	(0.007)	(0.018)	(0.007)
Panel 2. Parent's characteristics			
Household income	0.014	0.161	0.049
	(0.043)	(0.187)	(0.046)
Household wealth	-0.019	-0.427	-0.092
	(0.106)	(0.301)	(0.0101)
Hispanic	-0.003	-0.012	-0.004
	(0.006)	(0.022)	(0.006)
Non-white	-0.014	0.010	-0.012
	(0.009)	(0.025)	(0.009)
Years of education	-0.035	-0.219	-0.051
	(0.057)	(0.194)	(0.057)
Married	-0.004	-0.034	-0.010
	(0.010)	(0.024)	(0.009)
Number of kids	0.048	0.019	0.042
	(0.044)	(0.112)	(0.041)
Employed	-0.043**	-0.092**	-0.052**
	(0.021)	(0.045)	(0.022)
Num. of observations	42,773	7,527	50,260

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding 3 months around age 62). Each row pertains to each outcome based on separate regression. Column (A) shows regression discontinuity estimates for the U.S.-born (native) families, Column (B) for immigrant families, and Column (C) for entire sample. The numbers in each cell represent regression discontinuity estimates based on separate regression. Other covariates are not listed in the table. Data is sourced from HRS data from 1996 to 2018 years. Robust standard errors clustered at the parent level are in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 3.9. RDD estimates of the impact of the EEA on Social Security receipt

	(1)	(2)	(3)	
			Native	Immigrant
Treat	0.251***	0.269***	0.274***	0.174***
	(0.007)	(0.007)	(0.013)	(0.042)
Treat * Immigrant		-0.086***		
		(0.018)		
Immigrant		0.019***		
		(0.006)		
Number of observations	50,260	50,260	42,733	7,527

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding 3 months around age 62). The outcome is Social Security receipt, measured as a dichotomous variable (1 if a parent receives Social Security benefits, 0 otherwise). Column 1 represents a model identical to the preliminary model in Table 3.3. Column 2 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Column 3 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Column 3, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant families, respectively. “Treat” is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. “Immigrant” indicates a dummy variable indicating 1 if at least one parent is foreign-born (immigrant), otherwise 0. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.1. DRD subgroup analysis, by Social Security eligibility and gender

	(1) Eligible-Ineligible immigrants	(2) Male-Female immigrants
Panel 1. Parent–to–Child transfer		
Panel 1-1. Probability		
Treat	-0.032	0.010
	(0.039)	(0.013)
Treat * Eligible (or Male) immigrant	0.079*	0.024**
	(0.044)	(0.012)
Eligible (or Male) immigrant	0.055	0.042
	(0.034)	(0.037)
Panel 1-2. Amount		
Treat	565.392	286.253
	(678.873)	(912.85)
Treat * Eligible (or Male) immigrant	-650.369	-567.264
	(702.458)	(633.684)
Eligible (or Male) immigrant	-473.266	-127.908
	(520.858)	(127.991)
Panel 2. Child–to–Parent transfer		
Panel 2-1. Probability		
Treat	0.017	0.011
	(0.015)	(0.009)
Treat * Eligible (or Male) immigrant	-0.020	-0.034
	(0.018)	(0.023)
Eligible (or Male) immigrant	-0.018	-0.020*
	(0.016)	(0.011)
Panel 2-2. Amount		
Treat	270.660	64.509
	(209.998)	(73.701)
Treat * Eligible (or Male) immigrant	-469.139***	-527.720***
	(175.059)	(179.489)
Eligible (or Male) immigrant	-299.731***	-385.256**
	(62.465)	(172.869)
Donut hole size	3 months	3 months
Bandwidths	35 months	35 months
Total Num. of observations	7,527	7,527

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding 3 months around age 62). Sample is limited to immigrants. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. "Eligible" indicates a dummy variable indicating 1 if immigrants are Social Security eligible immigrants who have a 10-year U.S. work experience; "Male" indicates a dummy variable indicating 1 if immigrants are male. Each panel pertains to a specific transfer outcome. The numbers in each cell represent regression discontinuity estimates for each transfer outcome, obtained from separate regression. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.2. DRD subgroup analysis, by income level of adult children

	(A) U.S.-born (Native)	(B) Immigrant
Panel 1. Parent–to–Child transfer		
Panel 1-1. Probability		
Treat	-0.017	-0.013
	(0.017)	(0.025)
Treat * Low-income	0.047***	0.099***
	(0.012)	(0.034)
Low-income	0.010	0.026
	(0.010)	(0.016)
Panel 1-2. Amount		
Treat	245.759	267.505
	(298.123)	(756.907)
Treat * Low-income	-267.304	-645.589
	(160.777)	(692.157)
Low-income	-264.988***	-109.971
	(78.134)	(359.590)
Panel 2. Child–to–Parent transfer		
Panel 2-1. Probability		
Treat	0.011	0.006
	(0.013)	(0.008)
Treat * Low-income	-0.023	-0.018**
	(0.016)	(0.009)
Low-income	-0.021	-0.009
	(0.016)	(0.011)
Panel 2-2. Amount		
Treat	68.075	97.123
	(51.186)	(69.575)
Treat * Low-income	-67.681	-441.673***
	(58.515)	(114.366)
Low-income	81.252	-186.212
	(67.950)	(171.472)
Donut hole size	3 months	3 months
Bandwidths	35 months	35 months
Total Num. of observations	42,733	7,527

Note: The sample consists of non-coresident parent–child dyads where parents are between 59 and 64 years old (i.e., a 35-month age bandwidth excluding 3 months around age 62). “Treat” is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. "Low-income" indicates a dummy variable indicating 1 if whose parental annual income is less than $35,000. Column A indicates estimates for U.S-born subsample; Column B indicates estimates for immigrant subsample. Each panel pertains to a specific transfer outcome, obtained from separate regression. The numbers in each cell represent regression discontinuity estimates. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.3. RDD estimates of the impact of the EEA on transfers: cut-off age of 58

	Parent-to-child transfer		Child-to-parent transfer	
	(1) Probability	(2) Amount	(3) Probability	(4) Amount
Panel 1. Main model (*n*=52,005)				
Treat	0.025	58.973	0.006	-61.600
	(0.020)	(583.409)	(0.006)	(43.661)
Panel 2. Subgroup: Immigrant-Native				
Panel 2-1. DRD estimates (*n*=52,005)				
Treat	0.007	58.031	0.001	-4.580
	(0.011)	(159.107)	(0.004)	(17.578)
Treat * Immigrant	0.040	30.059	-0.008	-73.437
	(0.026)	(84.970)	(0.011)	(66.978)
Immigrant	0.066*	1262.084***	0.017*	192.280**
	(0.038)	(220.995)	(0.008)	(54.485)
Panel 2-2. Subgroup-based RDD				
Panel 2-2-1. Native (*n*=44,352)				
Treat	0.049	-119.171	-0.006	-56.014
	(0.032)	(645.737)	(0.006)	(41.910)
Panel 2-2-2. Immigrant (*n*=7,653)				
Treat	0.012	1,234.258	-0.002	-93.798
	(0.008)	(1,129.461)	(0.020)	(93.139)
Donut hole size	3 months	3 months	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months

Note: The sample consists of non-coresident parent–child dyads, where parental age is 35-months before and after age 58 excluding 3 months around age 58. Each column indicates each transfer outcome. *n* indicates sample size. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Panel 1 represents a model identical to the preliminary model in Table 3.3. Panel 2-1 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Panel 2-2 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Panel 2-2, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant individuals, respectively. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.4. RDD estimates of the impact of the EEA on transfers: cut-off age of 60

	Parent-to-child transfer		Child-to-parent transfer	
	(1) Probability	(2) Amount	(3) Probability	(4) Amount
Panel 1. Main model (*n*=50,192)				
Treat	-0.006	225.143	-0.004	-22.111
	(0.006)	(182.575)	(0.004)	(20.102)
Panel 2. Subgroup: Immigrant-Native				
Panel 2-1. DRD estimates (*n*=50,192)				
Treat	-0.009	-264.457	0.004	-8.131
	(0.007)	(243.704)	(0.004)	(15.311)
Treat * Immigrant	0.021	1,215.307	-0.003	-14.274
	(0.017)	(850.078)	(0.010)	(59.158)
Immigrant	0.043*	1347.516***	0.014**	187.578***
	(0.025)	(413.702)	(0.007)	(51.811)
Panel 2-2. Subgroup-based RDD				
Panel 2-2-1. Native (*n*=44,907)				
Treat	-0.009	54.981	-0.004	-18.366
	(0.007)	(174.607)	(0.004)	(13.959)
Panel 2-2-2. Immigrant (*n*=5,285)				
Treat	0.020	914.142	-0.019	-103.430
	(0.018)	(819.923)	(0.014)	(92.941)
Donut hole size	3 months	3 months	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months

Note: The sample consists of non-coresident parent–child dyads, where parental age is 35-months before and after age 60 excluding 3 months around age 60. Each column indicates each transfer outcome. *n* indicates sample size. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Panel 1 represents a model identical to the preliminary model in Table 3.3. Panel 2-1 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Panel 2-2 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Panel 2-2, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant individuals, respectively. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.5. RDD estimates of the impact of the EEA on transfers: cut-off age of 64

	Parent-to-child transfer		Child-to-parent transfer	
	(1) Probability	(2) Amount	(3) Probability	(4) Amount
Panel 1. Main model (*n*=51,805)				
Treat	-0.008	-117.504	0.000	9.668
	(0.006)	(134.391)	(0.003)	(20.102)
Panel 2. Subgroup: Immigrant-Native				
Panel 2-1. DRD estimates (*n*=51,805)				
Treat	-0.003	-43.318	-0.001	-1.897
	(0.007)	(119.982)	(0.003)	(21.232)
Treat * Immigrant	-0.025	-222.498	0.005	75.970
	(0.025)	(436.903)	(0.010)	(62.12)
Immigrant	0.015**	1540.386***	0.019*	253.810
	(0.007)	(524.131)	(0.011)	(247.763)
Panel 2-2. Subgroup-based RDD				
Panel 2-2-1. Native (*n*=43,146)				
Treat	-0.006	-63.813	-0.001	-20.530
	(0.007)	(131.309)	(0.003)	(21.242)
Panel 2-2-2. Immigrant (*n*=8,659)				
Treat	-0.021	-514.138	0.005	82.141
	(0.015)	(487.014)	(0.010)	(58.145)
Donut hole size	3 months	3 months	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months

Note: The sample consists of non-coresident parent–child dyads, where parental age is 35-months before and after age 64 excluding 3 months around age 64. Each column indicates each transfer outcome. *n* indicates sample size. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Panel 1 represents a model identical to the preliminary model in Table 3.3. Panel 2-1 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Panel 2-2 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Panel 2-2, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant individuals, respectively. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.6. RDD estimates of the impact of the EEA on transfers: cut-off age of 66

	Parent-to-child transfer		Child-to-parent transfer	
	(1) Probability	(2) Amount	(3) Probability	(4) Amount
Panel 1. Main model (*n*=52,347)				
Treat	0.001	-67.740	0.001	-12.427
	(0.006)	(163.064)	(0.002)	(16.868)
Panel 2. Subgroup: Immigrant-Native				
Panel 2-1. DRD estimates (*n*=52,347)				
Treat	0.001	-93.092	0.001	-8.582
	(0.006)	(148.073)	(0.003)	(17.239)
Treat * Immigrant	0.000	690.008	0.000	-24.312
	(0.000)	(475.812)	(0.000)	(58.979)
Immigrant	0.029*	1,185.187***	0.031*	203.196**
	(0.015)	(382.286)	(0.018)	(93.411)
Panel 2-2. Subgroup-based RDD				
Panel 2-2-1. Native (*n*=43,668)				
Treat	0.000	-190.132	0.003	-8.559
	(0.006)	(167.527)	(0.002)	(17.239)
Panel 2-2-2. Immigrant (*n*=8,679)				
Treat	0.003	620.433	0.010	32.750
	(0.014)	(520.612)	(0.008)	(57.880)
Donut hole size	3 months	3 months	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months

Note: The sample consists of non-coresident parent–child dyads, where parental age is 35-months before and after age 66 excluding 3 months around age 66. Each column indicates each transfer outcome. *n* indicates sample size. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Panel 1 represents a model identical to the preliminary model in Table 3.3. Panel 2-1 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Panel 2-2 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Panel 2-2, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant individuals, respectively. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.7. RDD estimates of the impact of the EEA on transfers: second-order polynomials

	Parent-to-child transfer		Child-to-parent transfer	
	(1) Probability	(2) Amount	(3) Probability	(4) Amount
Panel 1. Main model (*n*=50,260)				
Treat	0.024*	91.652	0.020	56.646
	(0.013)	(188.840)	(0.015)	(51.309)
R-squared	0.108	0.035	0.017	0.007
Panel 2. Subgroup: Immigrant-Native				
Panel 2-1. DRD estimates (*n*=50,260)				
Treat	0.024*	113.221	0.016*	19.242
	(0.013)	(320.472)	(0.009)	(32.714)
Treat * Immigrant	0.021	-325.756	-0.016	-267.791*
	(0.038)	(438.562)	(0.021)	(156.765)
Immigrant	0.030**	1,353.173**	0.018**	479.053*
	(0.013)	(618.171)	(0.009)	(274.317)
R-squared	0.120	0.041	0.018	0.006
Panel 2-2. Subgroup-based RDD				
Panel 2-2-1. Native (*n*=42,733)				
Treat	0.023*	55.538	0.013	31.942
	(0.013)	(66.912)	(0.012)	(40.247)
R-squared	0.095	0.039	0.014	0.004
Panel 2-2-2. Immigrant (*n*=7,527)				
Treat	0.018**	-187.063	-0.009	-232.949**
	(0.008)	(996.273)	(0.037)	(100.990)
R-squared	0.118	0.049	0.022	0.019
Donut hole size	3 months	3 months	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months

Note: The sample consists of non-coresident parent–child dyads, where parental age is 35-months before and after age 62 excluding 3 months around age 62. The second-order polynomials of age in months are used. *n* indicates sample size. Each column indicates each transfer outcome. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Panel 1 represents a model identical to the preliminary model in Table 3.3. Panel 2-1 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Panel 2-2 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Panel 2-2, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant individuals, respectively. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.8. RDD estimates of the impact of the EEA on transfers: third-order polynomials

	Parent-to-child transfer		Child-to-parent transfer	
	(1) Probability	(2) Amount	(3) Probability	(4) Amount
Panel 1. Main model (*n*=50,260)				
Treat	0.080**	280.297	0.011	97.058
	(0.039)	(287.444)	(0.013)	(98.231)
R-squared	0.117	0.040	0.015	0.007
Panel 2. Subgroup: Immigrant-Native				
Panel 2-1. DRD estimates (*n*=50,260)				
Treat	0.070**	224.114	0.013	45.682
	(0.030)	(364.049)	(0.012)	(44.215)
Treat * Immigrant	0.069	-262.181	-0.006	-532.316***
	(0.072)	(493.830)	(0.038)	(185.807)
Immigrant	0.039***	1,875.668***	0.037***	566.361**
	(0.011)	(400.963)	(0.012)	(269.350)
R-squared	0.112	0.035	0.019	0.007
Panel 2-2. Subgroup-based RDD				
Panel 2-2-1. Native (*n*=42,733)				
Treat	0.080**	212.517	0.018	149.088
	(0.039)	(324.698)	(0.020)	(171.619)
R-squared	0.099	0.045	0.012	0.005
Panel 2-2-2. Immigrant (*n*=7,527)				
Treat	0.062*	100.199	-0.003	-388.687***
	(0.035)	(644.131)	(0.046)	(99.866)
R-squared	0.117	0.045	0.022	0.020
Donut hole size	3 months	3 months	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months

Note: The sample consists of non-coresident parent–child dyads, where parental age is 35-months before and after age 62 excluding 3 months around age 62. The third-order polynomials of age in months are used. *n* indicates sample size. Each column indicates each transfer outcome. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Panel 1 represents a model identical to the preliminary model in Table 3.3. Panel 2-1 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Panel 2-2 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Panel 2-2, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant individuals, respectively. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Appendix Table A3.9. RDD estimates of the impact of the EEA on transfers: summary for main results

	Parent-to-child transfer		Child-to-parent transfer	
	(1) Probability	(2) Amount	(3) Probability	(4) Amount
Panel 1. Main model (*n*=50,260)				
Treat	0.020**	72.464	0.004	42.373
	(0.009)	(154.860)	(0.004)	(41.796)
R-squared	0.101	0.036	0.018	0.007
Panel 2. Subgroup: Immigrant-Native				
Panel 2-1. DRD estimates (*n*=50,260)				
Treat	0.019**	98.149	0.001	26.542
	(0.008)	(157.131)	(0.003)	(20.518)
Treat * Immigrant	0.007	-188.438	-0.006	-245.454***
	(0.006)	(552.168)	(0.011)	(84.155)
Immigrant	0.026*	1,444.802***	0.024***	299.731***
	(0.015)	(406.826)	(0.008)	(62.465)
R-squared	0.102	0.036	0.019	0.007
Panel 2-2. Subgroup-based RDD				
Panel 2-2-1. Native (*n*=42,733)				
Treat	0.020*	100.603	0.004	29.994
	(0.011)	(174.195)	(0.005)	(19.443)
R-squared	0.091	0.041	0.014	0.004
Panel 2-2-2. Immigrant (*n*=7,527)				
Treat	0.018*	-93.596	-0.010	-221.586***
	(0.010)	(1,312.878)	(0.014)	(82.359)
R-squared	0.117	0.048	0.023	0.019
Donut hole size	3 months	3 months	3 months	3 months
Bandwidths	35 months	35 months	35 months	35 months

Note: The sample consists of non-coresident parent–child dyads, where parental age is 35-months before and after age 62 excluding 3 months around age 62. The first-order of age in months are used. *n* indicates sample size. Each column indicates each transfer outcome. "Treat" is a dummy variable equal to 1 if the parent is over the cut-off age (age 62) and 0 otherwise. Panel 1 represents a model identical to the preliminary model in Table 3.3. Panel 2-1 represents a model which is the same as the difference-in-regression-discontinuity (DRD) model in Table 3.4. Panel 2-2 represents a model which is the same as the subgroup-based model with propensity score weights in Table 3.5. In Panel 2-2, covariates for each subgroup are weighted by the conditional probabilities of belonging to that subgroup, and "Native" and "Immigrant" refer to subset samples for U.S.-born and immigrant individuals, respectively. Other covariates are not listed in the table. Robust standard errors clustered at the parent level are in parentheses. Data is sourced from HRS data from 1996 to 2018 years. *** p<0.01 ** p<0.05 * p<0.1

Conclusion

This thesis consists of three papers that shed light on the interactions between intergenerational transfers, individuals' life events, and social policy, with a particular emphasis on differences between immigrant and U.S. native-born populations. The first paper describes differences in intergenerational transfers across immigrant and native families. Results show that immigrants are more engaged in child-to-parent and parent-to-child transfers than comparable natives, with a larger immigrant-native difference in child-to-parent transfers in parent-to-child transfers. Findings suggest that older immigrants in the U.S. rely more on familial support than U.S. native-borns and their immigrant children.

The second paper examines the impacts of life events on intergenerational transfers and the corresponding differences between immigrant and native families. Results present that a relatively larger number of transfer recipients' life events are associated with intergenerational transfers than transfer donors' life events. Immigrant and mixed-status families generally exhibit greater responsiveness to life events of transfer recipients compared to their native counterparts. Among several life events, a job loss is a consistent predictor of such immigrant-native differences.

The third paper investigates the effects of Social Security Earliest Eligible Age (age 62) on intergenerational transfers and associated immigrant-native differences. Results indicate an increase in parent-to-child transfers in response to Social Security. However, children in immigrant families decrease child-to-parent transfer while children in U.S.-born families do not. These effects are particularly pronounced for low-income families. Findings highlight the alleviating role of Social Security in reducing the financial support burden on children of immigrant, and the intergenerational redistributive effect of the Social Security program.

My dissertation offers social work policy and practice implications. The three papers collectively demonstrate that older immigrants heavily rely on intergenerational transfers, which are more responsive to job losses and U.S. social support programs than those of U.S. native-born individuals. These findings reveal the economic vulnerability of immigrants, which may be attributed to high unemployment risks and/or limited program eligibility. Furthermore, private transfers, in comparison to public transfers, are considered relatively volatile support sources, contingent on the financial circumstances of transfer donors. This instability leads to heightened economic fluctuations for older immigrants and arguably an elevated probability of intergenerational poverty transmission via intergenerational transfer patterns. To address this economic insufficiency, social policies may need to reassess eligibility rules, as current criteria are stricter for immigrants compared to natives.

In terms of social work practice, the findings underscore the importance of a social worker's role in securing and referring necessary resources to clients. Many vulnerable populations rely on private transfers within their families to address economic challenges, rendering their economic vulnerability less externally visible. Yet this familial dependence is quite unstable. Social workers thus need to assist these individuals in establishing more stable income streams by replacing their reliance on private transfers with state programs or other institutionalized resources.

References

Paper 1

Albertini, M., Mantovani, D., & Gasperoni, G. (2019). Intergenerational relations among immigrants in Europe: the role of ethnic differences, migration and acculturation. *Journal of Ethnic and Migration Studies*, *45*(10), 1693–1706. https://doi.org/10.1080/1369183X.2018.1485202

Altonji, B. J. G., Hayashi, F., & Kotlikoff, L. J. (1992). Is the Extended Family Altruistically Linked ? Direct Tests Using Micro Data. *The American Economic Review*, *82*(5), 1177–1198.

Amuedo-Dorantes, C., & Pozo, S. (2015). The impact of the recession on the wealth of older immigrant and native households in the United States. *IZA Journal of Labor Policy*, *4*(1). https://doi.org/10.1186/s40173-015-0033-x

Antecol, H., Kuhn, P., & Trejo, S. J. (2006). Assimilation via Prices or Quantities ? Sources of Immigrant Earnings Growth in Australia, Canada, and the United States. *The Journal of Human Resources*, *41*(4), 821–840.

Belotti, F., Deb, P., Manning, W. G., & Norton, E. C. (2015). twopm: Two-part models. *Stata Journal*, *15*(1), 3–20. https://doi.org/10.1177/1536867x1501500102

Berry, B. (2006). What accounts for race and ethnic differences in parental financial transfers to adult children in the United States? *Journal of Family Issues*, *27*(11), 1583–1604. https://doi.org/10.1177/0192513X06291498

Bitler, M., & Hoynes, H. (2015). Living arrangements, doubling up, and the great recession: Was this time different? *The American Economic Review*, *105*(5), 166–170. https://doi.org/10.1257/aer.p20151087

Bordone, V., & de Valk, H. A. G. (2016). Intergenerational support among migrant families in Europe. *European Journal of Ageing*, *13*(3), 259–270. https://doi.org/10.1007/s10433-016-0363-6

Borjas, G. J., & Chiswick, B. R. (1985). Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants. *Journal of Labor Economics*, *3*(4), 41–66. https://doi.org/10.1093/oso/9780198788072.003.0003

Brandt, M., & Deindl, C. (2013). Intergenerational Transfers to Adult Children in Europe: Do Social Policies Matter? *Journal of Marriage and Family*, *75*(1), 235–251. https://doi.org/10.1111/j.1741-3737.2012.01028.x

Burbidge, J. B., Magee, L., & Robb, A. L. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, *83*(401), 123–127. https://doi.org/10.1080/01621459.1988.10478575

Cherlin, A., Cumberworth, E., Morgan, P. P., & Wimer, C. (2013). The Effects of the Great Recession on Family Structure and Fertility. *Annals of the American Academy of Political and Social Science*, *650*(1), 214–231. https://doi.org/10.1177/0002716213500643

Chiswick, B. R., Le, A. T., & Miller, P. W. (2008). How immigrants fare across the earnings distribution in Australia and the United States. *Industrial and Labor Relations Review*, *61*(3), 353–373. https://doi.org/10.1177/001979390806100305

Cobb-Clark, D. A., & Hildebrand, V. A. (2006). The wealth and asset holdings of U.S.-born and foreign-born households: Evidence from SIPP data. *Review of Income and Wealth*, *52*(1), 17–42. https://doi.org/10.1111/j.1475-4991.2006.00174.x

Cobb-Clark, D. A., & Hildebrand, V. A. (2009). The asset portfolios of native-born and foreign-born Australian households. *Economic Record*, *85*(268), 46–59. https://doi.org/10.1111/j.1475-4932.2008.00528.x

Cox, D., & Rank, M. R. (1992). Inter-Vivos Transfers and Intergenerational Exchange. *The Review of Economics and Statistics*, *74*(2), 305–314.

Cragg, J. G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica*, *39*(5), 829. https://doi.org/10.2307/1909582

Deindl, C., & Brandt, M. (2011). Financial support and practical help between older parents and their middle-aged children in Europe. *Ageing and Society*, *31*(4), 645–662. https://doi.org/10.1017/S0144686X10001212

Dumon, W. A. (1989). Family and Migration. *International Migration*, *27*(2), 251–270. https://doi.org/10.1111/j.1468-2435.1989.tb00255.x

Florian, S. M., & Casper, L. M. (2016). Co-resident Grandparent Caring for Grandchildren: Variations by Race/Ethnicity, Gender, and Family Structure. *Proceedings of Population Association of America Annual Meeting*. https://paa.confex.com/paa/2016/meetingapp.cgi/Paper/8233

Glick, J. E., & Hook, J. (2007). Immigration and living arrangements: Moving beyond economic need versus acculturation. *Demography*, *44*(2), 225–249. https://doi.org/10.1353/dem.2007.0019

Goda, G. S., Golberstein, E., & Grabowski, D. C. (2011). Income and the utilization of long-term care services: Evidence from the Social Security benefit notch. *Journal of Health Economics*, *30*(4), 719–729. https://doi.org/10.1016/j.jhealeco.2011.04.001

Gustman, A. L., Steinmeier, T. L., & Tabatabai, N. (2012). How did the recession of 2007-2009 affect the wealth and retirement of the near retirement age population in the Health and Retirement Study? *Social Security Bulletin*, *72*(4), 47–66.

Haider, S. J., & McGarry, K. M. (2012). Parental investment in college and later cash transfer. *NBER Working Paper 18485*.

Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, *47*(1), 153–161. https://www.jstor.org/stable/1912352

Huang, X., Kaushal, N., & Wang, J. S. H. (2021). What Explains the Gap in Welfare Use Among Immigrants and Natives? *Population Research and Policy Review*, *40*(4), 819–860. https://doi.org/10.1007/s11113-020-09621-8

Hurd, M., Smith, J., & Zissimopoulos, J. (2011). Intervivos Giving Over the Lifecycle. *RAND Working Paper Series WR-524-1*. https://doi.org/10.7249/wr524-1

Isengard, B., König, R., & Szydlik, M. (2018). Money or space? Intergenerational transfers in a comparative perspective. *Housing Studies*, *33*(2), 178–200. https://doi.org/10.1080/02673037.2017.1365823

Kagitcibasi, C. (2005). Autonomy and relatedness in cultural context implications for self and family. *Journal of Cross-Cultural Psychology*, *36*(4), 403–422. https://doi.org/10.1177/0022022105275959

Kaushal, N. (2010). Elderly Immigrants' Labor Supply Response to Supplemental Security Income. *Journal of Policy Analysis and Management*, *29*(3), 451–478. https://doi.org/10.1002/pam

König, R., Isengard, B., & Szydlik, M. (2018). Migration Matters: Insights into Intergenerational Solidarity Patterns in Europe. In I. Crespi (Ed.), *Making Multicultural Families in Europe*. Palgrave Macmillan UK. https://doi.org/https://doi.org/10.1007/978-3-319-59755-3_14 2

Laferrère, A., & Wolff, F. C. (2006). Chapter 13 Microeconomic models of family transfers. In S.-C. Kolm & J. M. Ythier (Eds.), *Handbook of the Economics of Giving, Altruism and Reciprocity* (Vol. 2, pp. 889–969). Elsevier B.V. https://doi.org/10.1016/S1574-0714(06)02013-6

Laitner, J. (1997). Chapter 5 Intergenerational and interhousehold economic links. In M.R. Rosenzweig & 0. Stark (Eds.), *Handbook of Population and Family Economics* (pp. 189–238). Elsevier Science. https://doi.org/10.1016/S1574-003X(97)80022-0

Litwin, H., Vogel, C., Künemund, H., & Kohli, M. (2008). The balance of intergenerational exchange: Correlates of net transfers in Germany and Israel. *European Journal of Ageing*, *5*(2), 91–102. https://doi.org/10.1007/s10433-008-0079-3

McDonald, L. (2011). Theorising about ageing, family and immigration. *Ageing and Society*, *31*(7), 1180–1201. https://doi.org/10.1017/S0144686X11000511

McGarry, K. (2016). Dynamic aspects of family transfers. *Journal of Public Economics*, *137*, 1–13. https://doi.org/10.1016/j.jpubeco.2016.03.008

McGarry, K., & Schoeni, R. F. (1995). Transfer Behavior in the Health and Retirement Study : Measurement and the Redistribution of Resources within the Family. *The Journal of Human Resources*, *30*.

McKernan, S. M., Ratcliffe, C., Simms, M., & Zhang, S. (2014). Do Racial Disparities in Private Transfers Help Explain the Racial Wealth Gap? New Evidence From Longitudinal Data. *Demography*, *51*(3), 949–974. https://doi.org/10.1007/s13524-014-0296-7

McManus, P. A., & DiPrete, T. A. (2000). Market, family, and state sources of income instability in Germany and the United States. *Social Science Research*, *29*(3), 405–440. https://doi.org/10.1006/ssre.2000.0675

Merz, E. M., Özeke-Kocabas, E., Oort, F. J., & Schuengel, C. (2009). Intergenerational Family Solidarity: Value Differences Between Immigrant Groups and Generations. *Journal of*

Family Psychology, *23*(3), 291–300. https://doi.org/10.1037/a0015819

Migration Policy Institute. (2023). *Frequently Requested Statistics on Immigrants and Immigration in the United States*. https://www.migrationpolicy.org/article/frequently-requested-statistics-immigrants-and-immigration-united-states#immigrants_now_historically [Accessed 7th April 2023]

Nauck, B. (2001). Social Capital, Intergenerational Transmission and Intercultural Contact in Immigrant Families. *Journal of Comparative Family Studies*, *32*(4), 465–488.

OECD. (2022). International Migration Outlook 2021. *OECD Publishing.*

Puhani, P. A. (2000). The Heckman correction for sample selection and its critique. *Journal of Economic Surveys*, *14*(1), 53–68. https://doi.org/10.1111/1467-6419.00104

Raymo, J. M., Pike, I., & Liang, J. (2019). A New Look at the Living Arrangements of Older Americans Using Multistate Life Tables. *Journals of Gerontology - Series B*, *74*(7), 84–96. https://doi.org/10.1093/geronb/gby099

Schoeni, R. F. (2002). Does unemployment insurance displace familial assistance? *Public Choice*, *110*, 99–119. https://doi.org/10.1023/A:1013029325667

U.S. Department of Health and Human Services. (2022). Births in the United States. *NCHS Data Brief*, *442*, 1–8.

Vega, W. A. (1990). Hispanic Families in the 1980s: A Decade of Research. *Journal of Marriage and Family*, *52*(4), 1–23.

Wiemers, E. E. (2014). The Effect of Unemployment on Household Composition and Doubling Up. *Demography*, *51*(6), 2155–2178. https://doi.org/10.1007/s13524-014-0347-0

Wolff, F. C. (2019). First-generation immigrant transfers and mobility intentions: longitudinal evidence from France. *Journal of Ethnic and Migration Studies*, *45*(10), 1813–1831. https://doi.org/10.1080/1369183X.2018.1485208

Zissimopoulos, J., Thunell, J., & Mudrazija, S. (2020). Parental Income and Wealth Loss and Transfers to Their Young Adult Children. *Journal of Family and Economic Issues*, *41*(2), 316–331. https://doi.org/10.1007/s10834-019-09645-z

Paper 2

Altonji, J. G., Hayashi, F., & Kotlikoff, L. J. (1997). Parental altruism and inter vivos transfers: Theory and evidence. *Journal of Political Economy*, *105*(6), 1121–1166. https://doi.org/10.1086/516388

Altonji, J. G., & Villanueva, E. (2007). The Marginal Propensity to Spend on Adult Children. *The B.E. Journal of Economic Analysis & Policy*, *7*(1), 1–50. https://doi.org/10.2202/1935-1682.1488

Barajas, A., Chami, R., Fullenkamp, C., & Garg, A. (2010). The global financial crisis and workers' remittances to Africa: What's the damage? *Journal of African Development*, *12*(1), 173–175. https://doi.org/10.1057/s41308-019-00076-2

Bazzoli, G. J. (1985). The Early Retirement Decision: New Empirical Evidence on the Influence of Health. *The Journal of Human Resources*, *20*(2), 214–234. https://doi.org/10.2307/146009

Bound, J. (1991). Self-Reported Versus Objective Measures of Health in Retirement Models. *The Journal of Human Resources*, *26*(1), 106–138. https://doi.org/10.2307/145718

Bound, J., Schoenbaum, M., Stinebrickner, T. R., & Waidmann, T. (1999). The dynamic effects of health on the labor force transitions of older workers. *Labour Economics*, *6*(2), 179–202. https://doi.org/10.1016/S0927-5371(99)00015-9

Cherlin, A., Cumberworth, E., Morgan, P. P., & Wimer, C. (2013). The Effects of the Great Recession on Family Structure and Fertility. *Annals of the American Academy of Political and Social Science*, *650*(1), 214–231. https://doi.org/10.1177/0002716213500643

Chetty R, Stepner M, Abraham S, Lin S, Scuderi B, Turner N, Bergeron A, Cutler D. (2016). The Association Between Income and Life Expectancy in the United States, 2001-2014. *JAMA*, *315*(16), 1750-66. https://doi.org/10.1001/jama.2016.4226.

Cox, D. (1990). Intergenerational transfers and liquidity constraints. *Quarterly Journal of Economics*, *105*(1), 187–217. https://doi.org/10.2307/2937825

Cox, D., & Jappelli, T. (1990). Credit Rationing and Private Transfers: Evidence from Survey Data. *The Review of Economics and Statistics*, *72*(3), 445–454.

Davies, J. B. (1981). Uncertain Lifetime, Consumption, and Dissaving in Retirement. *Journal of Political Economy*, *89*(3), 561–577. https://doi.org/10.1086/260986

De, S., Quayyum, S., Schuettler, K., & Yousefi, S. R. (2019). Oil prices, growth, and remittance outflows from the Gulf Cooperation Council. *Economic Notes*, *48*(3), 1–17. https://doi.org/10.1111/ecno.12144

Dobkin, C., Finkelstein, A., Kluender, R., & Notowidigdo, M. J. (2018). The Economic Consequences of Hospital Admissions. *American Economic Review*, *108*(2), 308–352. https://doi.org/10.1257/aer.20161038

Edwards, K. A. (2020). Who helps the unemployed Workers' receipt of public and private transfers. *IZA Journal of Labor Economics*, *9*(1), 1–26. https://doi.org/10.2478/izajole-2020-0004

Fitzpatrick, M. D., & Moore, T. J. (2018). The mortality effects of retirement: Evidence from Social Security eligibility at age 62. *Journal of Public Economics*, *157*(December 2017), 121–137. https://doi.org/10.1016/j.jpubeco.2017.12.001

Frankel, J. (2011). Are Bilateral Remittances Countercyclical? *Open Economies Review*, *22*(1), 1–16. https://doi.org/10.1007/s11079-010-9184-y

Gill, F., & Shaeye, A. (2022). Relative Wages of Immigrant Men and the Great Recession. *Journal of Economics, Race, and Policy*, *5*(1), 1–12. https://doi.org/10.1007/s41996-020-00067-w

Gottlieb, A., Pilkauskas, N., & Garfinkel, I. (2014). Private financial transfers, family income, and the great recession. *Journal of Marriage and Family*, *76*(5), 1011–1024. https://doi.org/10.1111/jomf.12134

Insler, M. (2014). The health consequences of retirement. *Journal of Human Resources*, *49*(1), 195–233. https://doi.org/10.3368/jhr.49.1.195

Kpodar, K., Quayyum, S., Gammadigbe, V., & Mlachila, M. (2022). Defying the Odds: Remittances During the COVID-19 Pandemic. *The Journal of Development Studies*, 1–18. https://doi.org/10.5089/9781513578453.001

Laferrère, A., & Wolff, F. C. (2006). Chapter 13 Microeconomic models of family transfers. In S.-C. Kolm & J. M. Ythier (Eds.), *Handbook of the Economics of Giving, Altruism and Reciprocity* (Vol. 2, pp. 889–969). Elsevier B.V. https://doi.org/10.1016/S1574-0714(06)02013-6

Laitner, J. (1997). Chapter 5 Intergenerational and interhousehold economic links. In M.R. Rosenzweig & 0. Stark (Eds.), *Handbook of Population and Family Economics* (pp. 189–238). Elsevier Science. https://doi.org/10.1016/S1574-003X(97)80022-0

McDonald, L. (2011). Theorising about ageing, family and immigration. *Ageing and Society*, *31*(7), 1180–1201. https://doi.org/10.1017/S0144686X11000511

McGarry, K. (2004). Do changes in health affect retirement expectations? *The Journal of Human Resources*, *39*(3), 624–648.

McGarry, K. (2000). Testing Parental Altruism: Implications of a Dynamic Model. *NBER Working Paper 7593*.

McGarry, K. (2016). Dynamic aspects of family transfers. *Journal of Public Economics*, *137*, 1–13. https://doi.org/10.1016/j.jpubeco.2016.03.008

McGarry, K., & Schoeni, R. F. (1995). Transfer Behavior in the Health and Retirement Study : Measurement and the Redistribution of Resources within the Family. *The Journal of Human Resources*, *30*, 184–226.

Merz, E. M., Özeke-Kocabas, E., Oort, F. J., & Schuengel, C. (2009). Intergenerational Family

Solidarity: Value Differences Between Immigrant Groups and Generations. *Journal of Family Psychology*, *23*(3), 291–300. https://doi.org/10.1037/a0015819

Nauck, B. (2001). Social Capital, Intergenerational Transmission and Intercultural Contact in Immigrant Families. *Journal of Comparative Family Studies*, *32*(4), 465–488.

Neuman, K. (2008). Quit your job and get healthier? The effect of retirement on health. *Journal of Labor Research*, *29*(2), 177–201. https://doi.org/10.1007/s12122-007-9036-8

Orrenius, P. M., & Zavodny, M. (2010). Mexican immigrant employment outcomes over the business cycle. *American Economic Review*, *100*(2), 316–320. https://doi.org/10.1257/aer.100.2.316

Schaller, J., & Eck, C. (2021). Family Support in Hard Times: Dynamics of Intergenerational Exchange after Adverse Events. *NBER Working Paper 28295*. https://doi.org/10.2139/ssrn.3759832

Schoeni, R. F. (1997). Private interhousehold transfers of money and time: New empirical evidence. *Review of Income and Wealth*, *43*(4), 423–448. https://doi.org/10.1111/j.1475-4991.1997.tb00234.x

Waidmann, T., Bound, John, & Schoenbaum, M. (1995). The illusion of failure: Trends in the self-reported health of the U.S. elderly. *The Milbank Quarterly*, *73*(2), 187–198.

Wiemers, E. E. (2014). The Effect of Unemployment on Household Composition and Doubling Up. *Demography*, *51*(6), 2155–2178. https://doi.org/10.1007/s13524-014-0347-0

Yang, D., & Choi, H. J. (2007). Are remittances insurance? Evidence from rainfall shocks in the Philippines. *World Bank Economic Review*, *21*(2), 219–248. https://doi.org/10.1093/wber/lhm003

Zissimopoulos, J., Thunell, J., & Mudrazija, S. (2020). Parental Income and Wealth Loss and Transfers to Their Young Adult Children. *Journal of Family and Economic Issues*, *41*(2), 316–331. https://doi.org/10.1007/s10834-019-09645-z

Paper 3

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, *59*(2), 391–425. https://doi.org/10.1257/jel.20191450

Abramitzky, R., Boustan, L. P., & Eriksson, K. (2014). A nation of immigrants: Assimilation and economic outcomes in the age of mass migration. *Journal of Political Economy*, *122*(3), 467–506. https://doi.org/10.1086/675805

Albertini, M., Kohli, M., & Vogel, C. (2007). Intergenerational transfers of time and money in European families: Common patterns - Different regimes? *Journal of European Social Policy*, *17*(4), 319–334. https://doi.org/10.1177/0958928707081068

Albertini, M., Mantovani, D., & Gasperoni, G. (2019). Intergenerational relations among immigrants in Europe: the role of ethnic differences, migration and acculturation. *Journal of Ethnic and Migration Studies*, *45*(10), 1693–1706. https://doi.org/10.1080/1369183X.2018.1485202

Amuedo-Dorantes, C., & Juarez, L. (2013). Old-Age Government Transfers and the Crowding Out of Private Gifts: The 70 and Above Program for the Rural Elderly in Mexico. *Southern Economic Journal*, *81*(3), 782–801. https://doi.org/10.4284/0038-4038-2013.055

Amuedo-Dorantes, C., & Pozo, S. (2002). Precautionary Saving by Young Immigrants and Young Natives. *Southern Economic Journal*, *69*(1), 48–71. https://doi.org/10.2307/1061556

Barreca, A. I., Lindo, J. M., & Waddell, G. R. (2016). Heaping-induced bias in regression-discontinuity designs. *Economic Inquiry*, *54*(1), 268–293. https://doi.org/10.1111/ecin.12225

Barro, R. J. (1974). Are Government Bonds Net Wealth? *Journal of Political Economy*, *82*(6), 1095–1117.

Bartalotti, O., & Brummet, Q. (2017). Regression discontinuity designs with clustered data. *Advances in Econometrics*, *38*, 383–420. https://doi.org/10.1108/S0731-905320170000038017

Becker, G. S. (1974). A Theory of Social Interactions. *Journal of Political Economy*, *82*(6), 1063–1093.

Boatman, A., Claro, S., Fresard, M., & Kramer, J. W. (2022). Do Corequisite Math Courses Improve Academic Outcomes in Technical Colleges?: Evidence from Chile. *Research in Higher Education*, *63*(3), 453–480. https://doi.org/10.1007/s11162-021-09649-5

Calonico, S., Cattaneo, M. D., & Farrell, M. H. (2017). rdrobust : Software for regression-discontinuity designs. *The Stata Journal*, *17*(2), 372–404. https://doi.org/10.1177/1536867X1701700208

Calonico, S., Cattaneo, M. D., Farrell, M. H., & Titiunik, R. (2019). Regression discontinuity designs using covariates. *The Review OfEconomics and Statistics*, *101*(3), 442–451.

https://doi.org/10.1162/rest_a_00760

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica*, *82*(6), 2295–2326. https://doi.org/10.3982/ecta11757

Calonico, S., Cattaneo, M. D., Titiunik, R., Alonico, S. C., & Attaneo, M. D. C. (2015). Optimal Data-Driven Regression Discontinuity Plots. *Journal of the American Statistical Association*, *110*(512), 1753–1769. https://doi.org/10.1080/01621459.2015.1017578

Carril, A., Cazor, A., Gerardino, M. P., & Litschig, S. (2019). Subgroup analysis in regression discontinuity designs. *Working Paper*, 1–12. https://doi.org/10.13140/RG.2.2.33207.24483

Case, A., & Deaton, A. (1998). Large cash transfers to the elderly in South Africa. *Economic Journal*, *108*, 1330–1361. https://doi.org/10.1111/1468-0297.00345

Cattaneo, M. D., Titiunik, R., & Vazquez-Bare, G. (2017). Comparing Inference Approaches for RD Designs: A Reexamination of the Effect of Head Start on Child Mortality. *Journal of Policy Analysis and Management*, *36*(3), 643–681. https://doi.org/10.1002/pam.21985

Chuang, J. C. C. (2012). Do social allowance transfers crowd out private transfers? An analysis of responses among elderly households in Taiwan. *International Journal of Social Welfare*, *21*(2), 194–202. https://doi.org/10.1111/j.1468-2397.2011.00788.x

Cohen, L., & Iams, H. (2007). Income adequacy and social security differences between the foreign-born and U.S.-Born. *International Migration Review*, *41*(3), 553–578. https://doi.org/10.1111/j.1747-7379.2007.00085.x

Cox, Donal, & Jimenez, E. (1995). Private Transfers and the Effectiveness of Public Income Redistribution in the Philippines. In *Public spending and the poor: Theory and evidence*. Johns Hopkins University Press.

Cox, Donald, Eser, Z., & Jimenez, E. (1998). Motives for private transfers over the life cycle: An analytical framework and evidence for Peru. *Journal of Development Economics*, *55*(1), 57–80. https://doi.org/10.1016/S0304-3878(97)00056-4

Cox, Donald, Hansen, B. E., & Jimenez, E. (2004). How responsive are private transfers to income? Evidence from a laissez-faire economy. *Journal of Public Economics*, *88*, 2193–2219. https://doi.org/10.1016/S0047-2727(03)00069-0

Cox, Donald, & Jimenez, E. (1992). Social security and private transfers in developing countries: The case of Peru. *World Bank Economic Review*, *6*(1), 155–169. https://doi.org/10.1093/wber/6.1.155

Congressional Research Service. (2022). The Social Security Retirement Age. In *Congressional Research Service report*. 1-24. CRS Publication No. R44670.

Dumon, W. A. (1989). Family and Migration. *International Migration*, *27*(2), 251–270. https://doi.org/10.1111/j.1468-2435.1989.tb00255.x

Favreault, M., & Nichols, A. (2012). *Immigrant Diversity and Social Security: Recent Patterns and Future Prospects*. https://doi.org/10.2139/ssrn.1857036

Fitzpatrick, M. D., & Moore, T. J. (2018). The mortality effects of retirement: Evidence from Social Security eligibility at age 62. *Journal of Public Economics*, *157*(December 2017), 121–137. https://doi.org/10.1016/j.jpubeco.2017.12.001

Galiani, S., Gertler, P., & Bando, R. (2016). Non-contributory pensions. *Labour Economics*, *38*, 47–58. https://doi.org/10.1016/j.labeco.2015.11.003

Gelman, A., & Imbens, G. (2019). Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs. *Journal of Business and Economic Statistics*, *37*(3), 447–456. https://doi.org/10.1080/07350015.2017.1366909

Gibson, J., Olivia, S., & Rozelle, S. (2011). How widespread are nonlinear crowding out effects? the response of private transfers to income in four developing countries. *Applied Economics*, *43*(27), 4053–4068. https://doi.org/10.1080/00036841003800831

Goss, S. C. (2010). The future financial status of the social security program. *Social Security Bulletin*, *70*(3), 111–125.

Grembi, V., Nannicini, T., & Troiano, U. (2016). Do fiscal rules matter? *American Economic Journal: Applied Economics*, *8*(3), 1–30. https://doi.org/10.1257/app.20150076

Gulzar, S., Rueda, M. R., & Ruiz, N. A. (2021). Do Campaign Contribution Limits Curb the Influence of Money in Politics? *American Journal of Political Science*, *66*(4), 932–946. https://doi.org/10.1111/ajps.12596

Heim, B. T., Lurie, I. Z., & Ramnath, S. P. (2012). Immigrant-native differences in employment-based retirement plan participation. *Journal of Pension Economics and Finance*, *11*(3), 365–388. https://doi.org/10.1017/S147474721100062X

Hong, K., Dragan, K., & Glied, S. (2019). Seeing and hearing: The impacts of New York City's universal pre-kindergarten program on the health of low-income children. *Journal of Health Economics*, *64*, 93–107. https://doi.org/10.1016/j.jhealeco.2019.01.004

Jensen, R. T. (2003). Do private transfers "displace" the benefits of public transfers? Evidence from South Africa. *Journal of Public Economics*, *88*(1–2), 89–112. https://doi.org/10.1016/S0047-2727(02)00085-3

Juarez, L. (2009). Crowding out of private support to the elderly: Evidence from a demogrant in Mexico. *Journal of Public Economics*, *93*(3–4), 454–463. https://doi.org/10.1016/j.jpubeco.2008.10.002

Kaushal, N. (2014). How public pension affects elderly labor supply and well-being: Evidence from India. *World Development*, *56*, 214–225. https://doi.org/10.1016/j.worlddev.2013.10.029

Kim, S., & Koh, K. (2020). Does Early Access To Pension Wealth Improve Health? *Economic Inquiry*, *58*(4), 1783–1794. https://doi.org/10.1111/ecin.12903

Laferrère, A., & Wolff, F. C. (2006). Chapter 13 Microeconomic models of family transfers. In S.-C. Kolm & J. M. Ythier (Eds.), *Handbook of the Economics of Giving, Altruism and Reciprocity* (Vol. 2, pp. 889–969). Elsevier B.V. https://doi.org/10.1016/S1574-0714(06)02013-6

Lai, M. S., & Orsuwan, M. (2009). Examining the Impact of Taiwan's Cash Allowance Program on Private Households. *World Development*, *37*(7), 1250–1260. https://doi.org/10.1016/j.worlddev.2008.12.001

Laitner, J. (1997). Chapter 5 Intergenerational and interhousehold economic links. In M.R. Rosenzweig & 0. Stark (Eds.), *Handbook of Population and Family Economics* (pp. 189–238). Elsevier Science. https://doi.org/10.1016/S1574-003X(97)80022-0

Lee, D. S., & Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, *48*(1), 281–355. https://doi.org/10.1257/jel.48.2.281 Regression

Lee, S., Ku, I., & Shon, B. (2019). The Effects of Old-Age Public Transfer on the Well-Being of Older Adults: The Case of Social Pension in South Korea. *Journals of Gerontology - Series B*, *74*(3), 506–515. https://doi.org/10.1093/geronb/gbx104

Li, X., Hurd, M., & Loughran, D. S. (2008). *The Characteristics of Social Security Beneficiaries Who Claim Benefits at the Early Entitlement Age*. AARP working paper

Maitra, P., & Ray, R. (2003). The effect of transfers on household expenditure patterns and poverty in South Africa. *Journal of Development Economics*, *71*(1), 23–49. https://doi.org/10.1016/S0304-3878(02)00132-3

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, *142*(2), 698–714. https://doi.org/10.1016/j.jeconom.2007.05.005

Mejía-Guevara, I. (2015). Economic inequality and intergenerational transfers: Evidence from Mexico. *Journal of the Economics of Ageing*, *5*, 23–32. https://doi.org/10.1016/j.jeoa.2014.09.012

Merz, E. M., Özeke-Kocabas, E., Oort, F. J., & Schuengel, C. (2009). Intergenerational Family Solidarity: Value Differences Between Immigrant Groups and Generations. *Journal of Family Psychology*, *23*(3), 291–300. https://doi.org/10.1037/a0015819

Mudrazija, S. (2014). The balance of intergenerational family transfers: A life-cycle perspective. *European Journal of Ageing*, *11*(3), 249–259. https://doi.org/10.1007/s10433-013-0302-8

Mukherjee, A. (2022). Intergenerational Altruism and Retirement Transfers. *Journal of Human Resources*, *57*(5), 1466–1497. https://doi.org/10.3368/jhr.58.1.0419-10140R3

Nauck, B. (2001). Social Capital, Intergenerational Transmission and Intercultural Contact in Immigrant Families. *Journal of Comparative Family Studies*, *32*(4), 465–488.

Nikolov, P., & Adelman, A. (2019). Do private household transfers to the elderly respond to public pension benefits? Evidence from rural China. *The Journal of the Economics of Ageing*, *14*, 1-14. https://doi.org/10.1016/j.jeoa.2019.100204

Nikolov, P., & Bonci, M. (2020). Do public program benefits crowd out private transfers in developing countries? A critical review of recent evidence. *World Development*, *134*, 1-16. https://doi.org/10.1016/j.worlddev.2020.104967

Oruc, N. (2011). Do Social Transfers "Crowd-Out" Remittances: Evidence from Bosnia. *Seeu*

Review, *7*(1), 39–65.

Romig, K. (2022). *Social Security lifts more Americans above poverty than any other program*. Retrieved from https://waysandmeans.house.gov/sites/democrats.waysandmeans.house.gov/files/documents / CBPP- Kathleen Romig- SS lifts Americans above poverty.pdf

Roth, J., McCord, M. J., & Liber, D. (2007). The Landscape of Microinsurance in the World's 100 Poorest Countries. *The MicroInsurance Centre*, 1–97.

Sánchez, G. E. (2022). Non-compliance notifications and taxpayer strategic behavior: evidence from Ecuador. *International Tax and Public Finance*, *29*(3), 627–666. https://doi.org/10.1007/s10797-021-09677-y

Schoeni, R. F. (2002). Does unemployment insurance displace familial assistance? *Public Choice*, *110*, 99–119. https://doi.org/10.1023/A:1013029325667

Sevak, P., & Schmidt, L. (2014). Immigrants and retirement resources. *Social Security Bulletin*, *74*(1), 27–45.

Skovron, C., & Titiunik, R. (2015). A Practical Guide to Regression Discontinuity Designs in Political Science. *Working Paper*, 1–40.

Smythe, A. (2019). The Impact of Social Security Eligibility on Transfers to Elderly Parents and Wealth -building among Adult Children. *Center for Financial Security Working Paper (University of Wisconsin-Madison)*.

Social Security Administration. (2021). *Population profile*. Retrieved from https://www.ssa.gov/policy/docs/population-profiles/never-beneficiaries.html

Social Security Administration. (2022). *Annual Statistical Supplement to the Social Security Bulletin, 2022*. SSA Publication No. 13-11700. Social Security Administration, Washington, DC.

U.S. Census Bureau. (2019). *Income and Poverty in the United States: 2018*. U.S. Government Publishing Office, Washington, DC.

Whitman, K., Reznik, G. L., & Shoffner, D. (2011). Who never receives social security benefits? *Social Security Bulletin*, *71*(2), 17–24.